Hindawi
Mobile Information Systems
Volume 2022, Article ID 1283040, 16 pages
https://doi.org/10.1155/2022/1283040

Research Article

Analysis System of MICE Tourism Economic Development Strategy Based on Machine Learning Algorithm

Bin Hu[1] and Bin Yan[2]

[1]*Department of Foreign Language and Tourism, Hebei Petroleum University of Technology, Chengde 067000, Hebei, China*
[2]*Department of Management Engineering, Hebei Petroleum University of Technology, Chengde 067000, Hebei, China*

Correspondence should be addressed to Bin Yan; yanbin@cdpc.edu.cn

Received 29 April 2022; Revised 27 June 2022; Accepted 3 August 2022; Published 30 August 2022

Academic Editor: Mian Ahmad Jan

The environmental effect of the meetings, incentives, conventions, and exhibitions (MICE) industry is as extensive as its economic impact. Visitors attending events use a wide range of service providers, including airline car rental firms, restaurants, hotels, theaters, and tour operators. Traditionally used tourism demand forecasting approaches rely heavily on univariate time series and multivariate regression models. Although these function-based prediction systems have demonstrated some effectiveness in forecasting tourism, they are unable to accurately capture the link between tourist demand and supply as a feed-forward neural network does (FFNN). Research has shown that an FFNN can outperform regression and time-series algorithms when it comes to forecasting tourism data. This research, for the first time, expands the use of neural networks in tourist demand creation by combining a hybrid FFNN and chimp optimization learning algorithm (i.e., FFNN-ChOA) into a nonlinear tourism demand dataset. In terms of predicting accuracy, FFNN-ChOA surpasses traditional backpropagation neural networks, regression models, and time-series models.

1. Introduction

No amount of unsold plane tickets or empty hotel rooms can be stored. Short- and long-term business predictions are critical in the tourist sector because of their cyclical nature. Researchers in tourism have attempted to apply several mathematical methodologies to depict the quantitative link between one demand and its antecedents. Alternatively, a connection analysis for the regression model might be built entirely on its historical performance. The previous performance of these relationship models is then utilized to anticipate or predict future performance. Building a relationship model is only possible if you have a wealth of data at your disposal, much of which should be old [1, 2].

In the past, manual (or visual) link detection methods included desk analysis of raw data, phrase identification (looking for keywords), and an ad hoc search for distinct patterns. The downside is that these methods of manually identifying relationships are cumbersome and time-consuming. Tourism scholars and practitioners are frequently confronted with a mountain of raw information. In the tourist business, automated link identification is almost never employed [3]. Instead, past research has relied heavily on appropriate time-series models and multiple regression analyses to predict and anticipate relationships. Models that utilize time-series data to predict future outcomes do not make any assumptions about other variables; instead, they use historical data to create a mathematical function that depicts how a variable has performed in the past. Estimated values can be forecasted using the created function [4].

For forecasting purposes, time-series models perform relatively well because of their simplicity. As a result, it is impossible to use time-series forecasting models to make accurate predictions about the future. An independent variable and a group of dependent variables are linked together in a multiplex mathematical equation in multiple regression analysis models. The dependent variable's future values can be predicted using this function [5]. Developing a multiple regression model that incorporates economic elements, such as income and travel costs, is known as an econometric model. There are some drawbacks to using multivariate regression models, notwithstanding their great explanatory power and strong prediction accuracy; multiple interactions among some of the independent factors and challenges with data collection are the two most significant drawbacks of this study [6].

Modeling the human brain's ability to learn is done using neural networks [7, 8]. Many basic functional units (called nodes) operate in parallel without any central control in a neural network. The weights of the interconnections between nodes can be changed during the learning process. An effective neural network is a function of the connection technique and the type of the processing elements it uses. An FFNN, for example, has connections that create an acyclic graph that may express linearly separable functions [9]. Underwater sound processing, robotics, marine animal identification, wireless networks, and sonar target recognition have all benefited from the use of neural networks. To better predict overnight backcountry stays in US national parks, researchers [10] used an ANN in their investigation. As a result of their research, the researchers concluded that using a backpropagation ANN with weekly time-series data can improve predicting accuracy significantly [11]. A comparatively small number of articles have employed neural networks for tourism demand prediction [12]. It was shown that an FFNN might be used to simulate the Chinese desire to travel to Honk Kong (expressed by a lower-dimensional function). Annual Japanese arrivals were predicted more accurately using the FFNN model than with multiple regression or naïve models such as the simple moving average or exponent smoothing, according to the researchers in Reference [3]. ANNs and nonlinearly separable data have never been linked in a published study before, but that may soon change. Indicative trends can be seen in linearly separable data sets that can be represented by linear functions. A linearly separable function cannot reflect all of the data in the tourism demand spectrum. Hence, the fundamental goal of this study is to examine whether a hybrid FFNN and chimp optimization learning method can be used to predict the connection of nonlinearly distinguishable data in tourism demand. By using FFNN-ChOA in conjunction with externally supplied real data, an FFNN may be further extended. Using the feedback, the weights are then recalculated from the output nodes to the hidden node(s) until the network properly categorizes all training patterns.

According to Reference [13], there are two primary groups of metaheuristic algorithms: single-solution and population-based. In the earlier category, the search process begins with a single feasible solution. This single potential solution is then enhanced through iterations. In contrast, population-based algorithms optimize utilizing a set of solutions. In this instance, the search procedure begins with an initial random population (many options), which is then improved through iterations. Population-based metaheuristics offer several benefits over single-solution algorithms:

(i) Multiple solutions communicate knowledge about the search area, resulting in abrupt jumps toward the attractive portion of the search area

(ii) Multiple optimal solutions collaborate to prevent locally optimum solutions

(iii) Generally, population-based algorithms are more exploratory than single-solution optimization algorithms

Swarm Intelligence Algorithm is one of the most intriguing subfields of population-based algorithms (SIA).

However, in this paper, we try to divide the meta-heuristic algorithm by its nature-inspiring origin, as previous authoritative references have made these categories in other ways [14, 15]. In this kind of categorization, there are both single-vector and swarm methods in each category. For example, in the physic-based category, there is GA (population-based) and SA (single-solution-based).

Generally, ChOA has some advantages over other MOAs which has motivated us to use this algorithm for the mentioned problem. Actually, the ability and intelligence of chimpanzees are not identical, but they all do their duties as participants of a group of hunters. Consequently, each participant's aptitude may be valuable during a particular stage of the search event. Our motivation can be summed up in five major reasons: clarity, adaptability, mathematical notation process, avoidance of local optima, and the NFL theorem.

Following a discussion of tourism demand forecasting approaches and the motives for this investigation, the remaining portions of this paper are arranged as follows. It begins with an examination of the functions of the ChOA algorithm and FFNN. As valuable as an FFNN maybe, its capacity to analyze nonlinear data is severely limited. Learning processes for the FFNN-ChOA, a modification of the FFNN that can analyze data in any function, will be discussed next. To model and estimate the demand for Japanese tourists to Thailand, an FFNN-ChOA is constructed using publicly available data (nonlinearly distinguishable data with a shock). This section explains how to build a model from scratch. The empirical results section, which depends on the data obtained from this research, follows to display the experimental results of prediction performance. There are three ways to quantify the accuracy of predicting results: mean absolute deviation, root mean square deviation, and mean absolute percentage error. The findings predicted by the FFNN-ChOA model are then evaluated with those predicted by FFNN and other frequently used regression and time-series global visitors demand prediction models. When it comes to forecasting demand for Japanese tourists' visits to Thailand, the research report and the practicability of an FFNN-ChOA are examined. Finally, in the concluding section, the significance of this investigation is discussed and future research possibilities are suggested.

2. Background Materials

2.1. FFNN for MICE Evaluation Model. Multiple variables have an effect on MICE; nevertheless, the processes by which they do so remain unknown. FFNNs are ideally suited to identifying MICE because of their "black box" mapping of

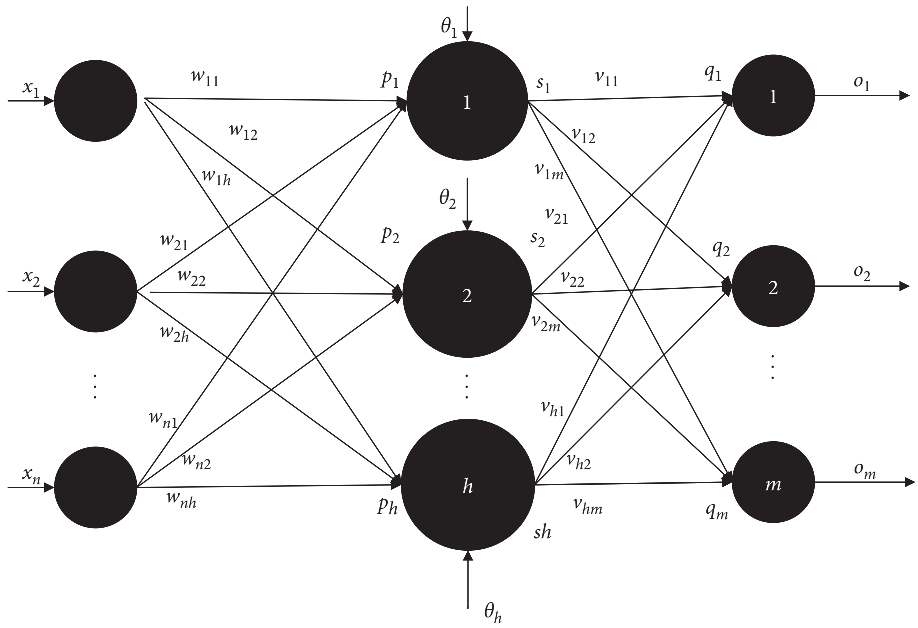


Figure 1: XRD patterns of calcium oxide expansion agent samples.

input to output. This research develops an MICE rating model using a metaheuristic-based FFNN.

There are exactly as many input nodes as there are inputs in this structure. Until now, there is no defined way to determine the quantity of hiding layer nodes. This value range may be determined using

$$\text{Hid} - \text{Node} = \sqrt{\text{No} - \text{in} + \text{NO} - \text{out}} + \phi, \tag{1}$$

where No − in stands for the input layer's number of nodes, ϕ denotes the bias nodes and oNO − out stands for the output layer's number of nodes, according to the aforesaid technique and simulation results. Additionally, the Kolmogorov theorem [1] enables the formulation for determining the number of hidden layer nodes, as follows:

$$\text{Hid} - \text{Node} = 2 \times (\text{No} - \text{in}) + 1. \tag{2}$$

The FFNN-based MICE assessment model was created utilizing the data from the previous paragraph, as shown in Figure 1. As observed in this picture, feed-forward NNs (FFNNs) feature one-way interconnection. The FFNN outcomes are calculated using

$$p_j = \sum_{i=1}^{n} \left(X_i \times W_{ij} \right) - \theta_j, \tag{3}$$

where W_{ij} stands for the weight vectors from the i-th input terminal to the j-th hidden node, whilst X_i stands for the i-th node's input and θ_j represents the j-th hidden node's bias. According to equation (4), a sigmoid function is used to calculate each hidden layer node's output:

$$s_j = \frac{1}{e^{-p_j} + 1}. \tag{4}$$

Once the concealed nodes' outputs have been computed, the final result may be determined as follows:

$$\begin{aligned} q_k &= \sum_{j=1}^{h} s_j W_{jk}, \\ O_k &= \frac{1}{e^{-q_k} + 1}. \end{aligned} \tag{5}$$

The most crucial components of FFNNs are their biases and weights. The connection weight vectors for each node must be set to the optimum values when employing an FFNN.

2.2. Chimp Optimization Algorithm. Fission-fusion is a group that includes chimpanzees. There is a constant flux in the social structure in this sort of society. A person's ability and responsibility may change with time, like the rest of society in general. The concept of subgroups is introduced in this algorithm because each chimpanzee group will have its own unique potential to do a given job [16].

Driving, blocking, chasing, and attacking chimpanzees are the four classifications. To guarantee a successful search, they are given a range of tasks. Following their prey instead of attempting to grab them, drivers are content to keep up with them. Barricade's built-in trees obstruct the prey's escape route. Chasers want to capture their prey swiftly. Finally, the prey's escape path into the lower woodland has been discovered by the predators. Figure 2 depicts the process of hunting at several points along the way. When chimpanzees hunt in groups, they go through two unique stages: "Exploration," in which they drive and block the prey while following it, and "Exploitation," in which they attack the prey.

2.2.1. The Mathematical Model of ChOA. As previously indicated, prey is pursued throughout the exploratory and exploitative periods. Push and pursue the prey with the help of equations (6) and (7):

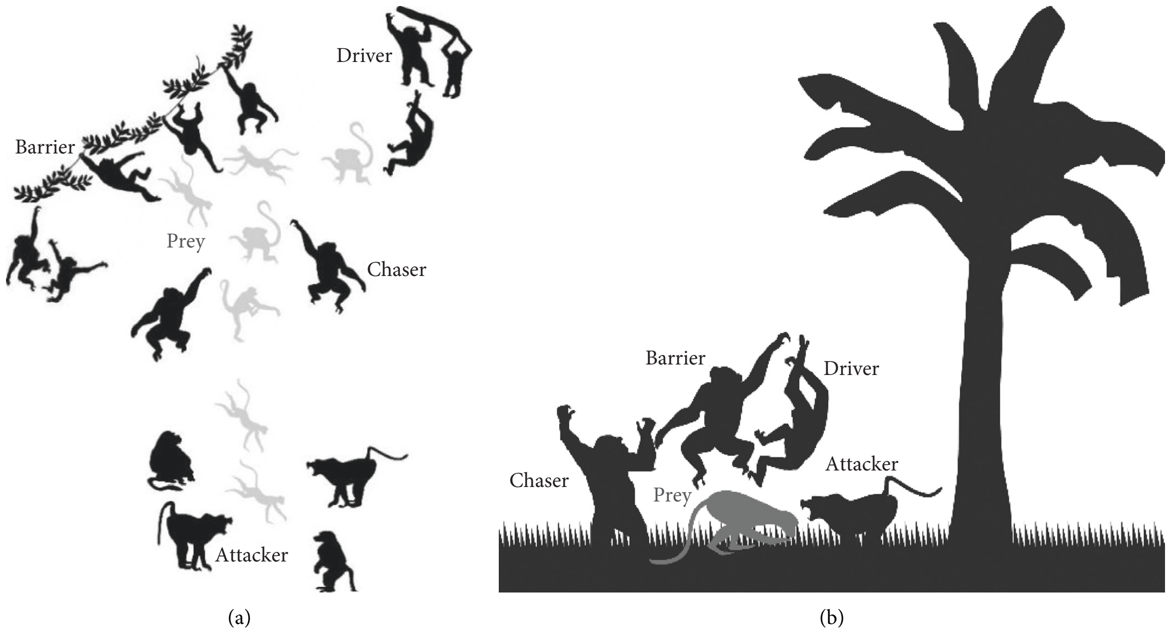


FIGURE 2: "Exploration" vs. "Exploitation."(a) Exploration (b) Exploitation.

$$\mathbf{d} = \left| -\mathbf{x}_{\text{chimp}}(t) \cdot \mathbf{m} + \mathbf{x}_{\text{prey}}(t) \cdot \mathbf{c} \right|, \tag{6}$$

$$\mathbf{x}_{\text{chimp}}(t+1) = -\mathbf{d}.\mathbf{a} + \mathbf{x}_{\text{prey}}(t), \tag{7}$$

where $\mathbf{x}_{\text{prey}}$ and $\mathbf{x}_{\text{chimp}}$ are, respectively, the prey and the chimp position vectors, t denotes the number of iterations, and **a, m,** and **c** are the coefficient vectors, which can be represented as follows:

$$\begin{aligned} \mathbf{a} &= 2.\mathbf{r}_1 \cdot \mathbf{f} - \mathbf{a}, \\ \mathbf{m} &= \mathbf{Chaos\_value}, \\ \mathbf{c} &= 2.\mathbf{r}_2. \end{aligned} \tag{8}$$

The **f** parameter is nonlinearly reduced by the iteration from 2.5 to 0. Furthermore, the range of the randomized variables $\mathbf{r_1}$ and $\mathbf{r_2}$ is [0, 1]. These random coefficients prevent the algorithm from getting stuck in local minima. These numerous chaotic maps reveal the effect of chimpanzees' sexual desires on hunting behavior in the form of this chaotic vector, **m**.

fs dynamic behavior may be seen in Table 1 and Figure 3. As you can see, T represents the maximum number of iterations, and t represents the current iteration. To improve the ChOAs' performance, a range of curves and slopes were used to pick **f** coefficients.

Among all mathematical optimization techniques, locating the global optimum is a typical and difficult problem. Generally, there are two essential phases that define the preferred path to convergence toward the global optimum in population-based optimization approaches (Exploration and Exploitation). The participants must be urged to disperse through the whole search area in the initial phases of minimization. In other words, rather than concentrating on local optimal solution, they ought to strive to investigate the entire search area. The participants must use the knowledge they have obtained in the later rounds to reach the global optimum. In ChOA, we may optimize these two main phases to discover global optimum with quick convergence speed by

TABLE 1: f vectors.

Group	f
Attacker	$1.95{-}2\ t^{1/4}/T^{1/3}$
Barrier	$1.95{-}2\ t^{1/4}/T^{1/3}$
Driver	$(-3\ t^3/T^3) + 1.5$
Chaser	$(-2\ t^3/T^3) + 1.5$

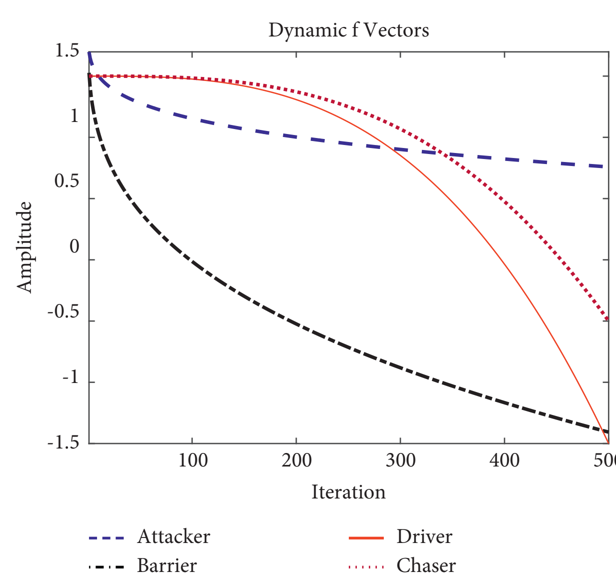


FIGURE 3: Dynamic coefficients **f**.

fine-tuning the parameter **f**. In light of these considerations, we put forth the assailant, obstacle, follower, and driver of the independent groups' model.

Each set of entities in this approach independently attempts to search the problem area using a strategy focused on adjusting *f*. Particles can be thought of as a group with a coherent approach because they all exhibit the same behavior in local and global search in standard population-based techniques. However, any population-based algorithm might theoretically produce more random and guided search at the same time if it used various independent subgroups with a common purpose. In this study, using various methods for updating f, we theoretically model the independent subgroups. In other words, the subgroups act differently in terms of how thoroughly they complete their tasks including exploration and exploitation. Any continuous function having a range between [0, L] can be used to implement the updating techniques of independent subgroups.

Before they can try to catch the prey, they must first locate it by driving or blocking it; then, they must encircle it until they determine its location. The search is conducted by intruders. Driver, barrier, and chaser may all be involved in a chase at times. The proper location of the prey is unknown in the first iteration. In order to deal with this issue, it is reasonable to assume that the attacker will be in the same place as the prey. Driver, barrier, and chaser locations should be updated based on the attacker's location. To keep the best answers, other chimpanzees are prompted by the best chimpanzees to change their positions. Equations (9) to (11) characterize this strategy as follows:

$$\begin{aligned} d_{\text{Barrier}} &= \left|x_{\text{Barrier}} \times c_2 - x \times m_2\right| \\ d_{\text{Attacker}} &= \left|x_{Attacker} \times c_1 - x \times m_1\right| \\ d_{\text{Driver}} &= \left|x_{\text{Driver}} \times c_4 - x \times m_4\right| \\ d_{\text{Chaser}} &= \left|x_{\text{Chaser}} \times c_3 - x \times m_3\right|, \end{aligned} \tag{9}$$

$$\begin{aligned} x_1 &= -a_1 \times d_{\text{Attacker}} + x_{\text{Attacker}} \\ x_2 &= -a_2 \times d_{\text{Barrier}} + x_{\text{Barrier}} \\ x_3 &= -a_3 \times d_{\text{Chaser}} + x_{\text{Chaser}} \\ x_3 &= -a_4 \times d_{\text{Driver}} + x_{\text{Driver}}. \end{aligned} \tag{10}$$

$$\mathbf{x}(t+1) = \langle \mathbf{x}_1 + \mathbf{x}_2 + \mathbf{x}_3 + \mathbf{x}_4 \rangle \times \frac{1}{4}, \tag{11}$$

Search agents' positions are always up to date because the chimpanzees in the search area regularly change their positions with respect to one another, as seen in Figure 4. As searching agents move in a circle, the chimpanzee's final location may be seen.

The chimpanzees will assault and pursue prey till the victim comes to a stop, as was previously indicated. It is necessary to drop the value of f linearly to replicate the attack process. While f drops from 2.5 to 0 in subsequent rounds, it is random in the range [−2**f**, 2**f**]. Figure 4 shows that a chimpanzee's future location can be anywhere between

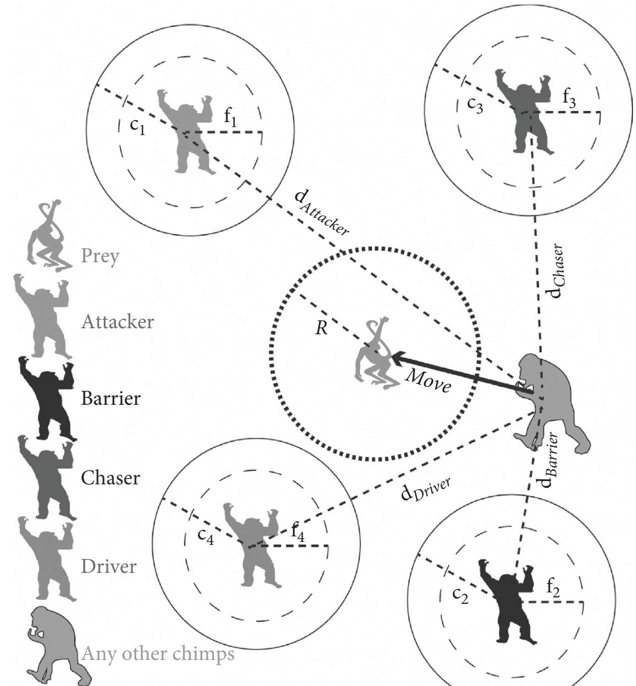


Figure 4: Chimp's position updating process.

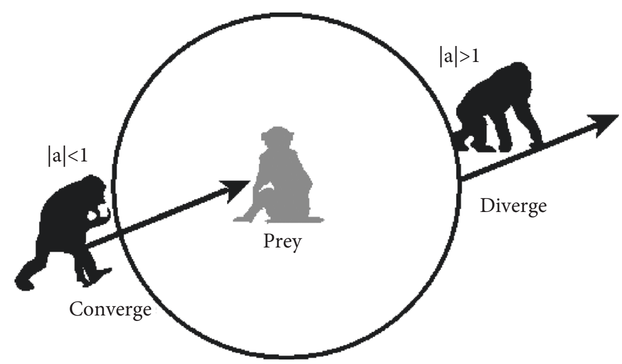


Figure 5: Searching behavior considering vector values.

[−1, 1] depending on the distribution of random integers. Despite the recommended driving techniques, ChOA could still be a chance of being caught in local minima. "Exploration" is the term used to describe this period. As a result, ChOA requires an extra operator in order to avoid becoming entangled in locally optimal solutions and assure exploration success.

Chimpanzees in the ChOA move in various directions to discover their prey and then unite to attack it. This action is theoretically illustrated in Figure 5 by assigning the vector "**a**" in such a manner that becoming stranded in local minima, the chimps disperse from their prey and compel individuals to rejoin at the location of their prey.

As previously stated, chimpanzees' social motivation is based on the hunt for food. Because the last piece of hunting meat is so valuable, the chimpanzees are obligated to give up their hunts. As a result, they engage in a frantic snatching of flesh for collective nourishment. Finally, chimpanzee psychosis may be simulated using chaos maps.

Figure 6 and Table 2 detail the chaotic maps used to improve the ChOA's efficiency. These systems, although predictable, are capable of producing unpredictable results. The initial value of 0.7 is shared by all chaotic maps. Here is a visual representation of the updating process:

$$\mathbf{x}_{\mathrm{chimp}}(t+1) = \begin{cases} \textbf{Chatic\_value} & \text{if } \mu > \dfrac{1}{2} \\ & , \\ \mathbf{x}_{\mathrm{prey}}(t) - \mathbf{a}.\mathbf{d} & \text{if } \mu < \dfrac{1}{2} \end{cases} \tag{12}$$

where μ represents a randomized number between 0 and 1.

In this equation, the normal behavior of chimp for changing position $\mathbf{x}_{\mathrm{chimp}}(t+1) = \mathbf{x}_{\mathrm{prey}}(t) - \mathbf{a}.\mathbf{d}$. is substituted by values from the chaotic map (**Chaotic_value**) to provide chaotic behaviors for justification of sexual motivation of chimp. Indeed, this term reduces the risk of getting stuck in local minima by changing the search space, chaotically [17]. In fact, by using the chaotic maps, we can control how the search space is changed in addition to the random behavior.

To summarize, ChOA begins with the creation of a random chimpanzee population (candidate solutions). All chimpanzees are then classified as attackers, barriers, chasers, or drivers, depending on their general mannerisms and habits. When it comes to updating their coefficient of variation, the chimpanzee groups adopt a unique strategy ($\mathbf{f}$). In this repeated process, the prey's position is guessed by the attacker, the barrier, the pursuit, and even the driver. Updates are made to the prey's distance from each of the available solutions. Use an adaptive modification of the parameters $\mathbf{c}$ and $\mathbf{m}$ to avoid local optima. As a further speed-up, the amount of $\mathbf{f}$ has been reduced from 2.5 to zero. Otherwise, they would all rush toward the food if it were available. Finally, the use of chaotic maps speeds up convergence by preventing local minima from forming.

3. Methodology

3.1. Training an FFNN Using ChOA. In this section, the proposed FFNN-ChOA training method for the FFNN is discussed. ChOA is used to train an FFNN with just a hidden unit. The effectiveness of this training technique relies heavily on ChOA's depiction of FFNN elements (search agents) and its objective function selection.

In order to encode all the different FFNN weights and biases for each individual chimpanzee, we use a one-dimensional vector for each one. For each vector, the total length may be calculated using equation (13). For example, equation (14) produces the FFNN ultimate vector seen in Figure 7, which illustrates this encoding strategy:

$$\mathrm{Length} = (n-h) + (2-h) + 1, \tag{13}$$

$$\mathrm{Chimp} = [w_1 w_2 w_3 \ldots w_{11} w_{12} b_1 b_2 b_3 b_4 b_5 b_6]. \tag{14}$$

MSE is used to evaluate the chimpanzees' performance, which is carried out by calculating the difference between the needed and evaluated values for all training samples that were generated by the search engines (FFNNs). An MSE solution is shown in

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (f_r - f_e)^2. \tag{15}$$

3.2. Dataset. Official sources from Japan and Thailand were utilized to learn about and test various network configurations in this study. It was important to choose data that were available, reliable, and capable of being quantified during the modeling process. According to the following sources, Table 3 contains essential information about the Japanese number of tourists to Thailand between 1991 and 2020 [18].

(i) The Thailand Tourist Association's Statistical Report of Tourism (1991–2020)
(ii) The Thailand Government's Department of Statistics issued the Director of Internal Revenue Annual Survey (1991–2020)
(iii) Thailand Tourist Organization Executive Summary (1991–2020) from the Thailand Tourist Organization
(iv) Japan's Executive Yuan Accounting and Statistics publishes the Republic of China's Statistical Handbook (1991–2020)
(v) The Finance and Information of the Executive Yen of Japan publishes the Monthly Journal of Information of the Japanese government (1995–2020)
(vi) Thailand Tourist Association's Visitor Arrival Statistics (1991–2020)

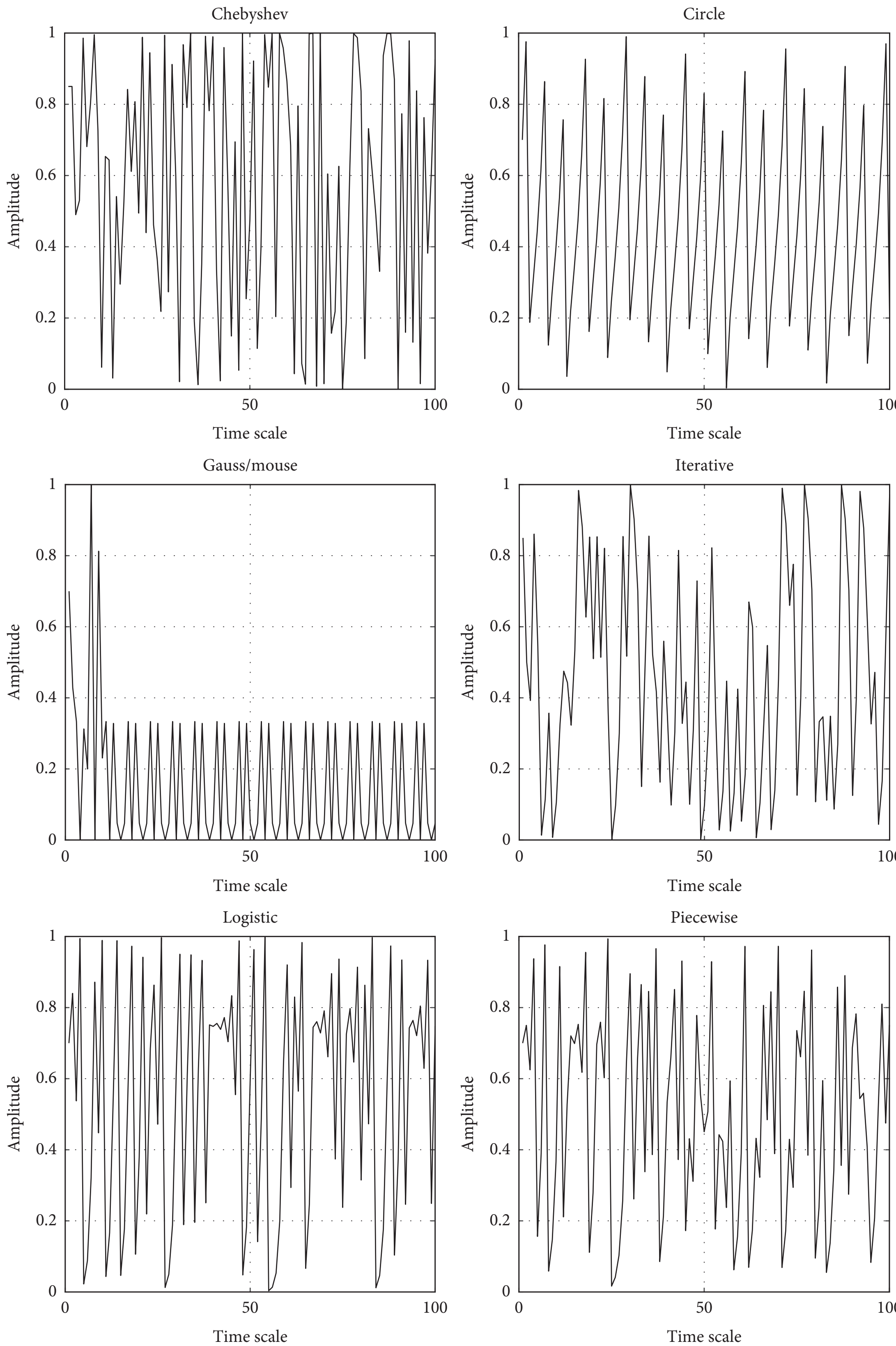
Because of the USD/Yen floating currency, this research, like the previous one that used FFNNs to anticipate tourism demand (Law and Au, 1999), measures all monetary values in USD. The number of Japanese visitors to Thailand may be shown as a function of the following:

$$\begin{aligned} Arrival = f\,(&SEPR, FORER, POPU, MAEX, \\ &GDP, AVEHR), \end{aligned} \tag{16}$$

where information is summarized in Table 4.

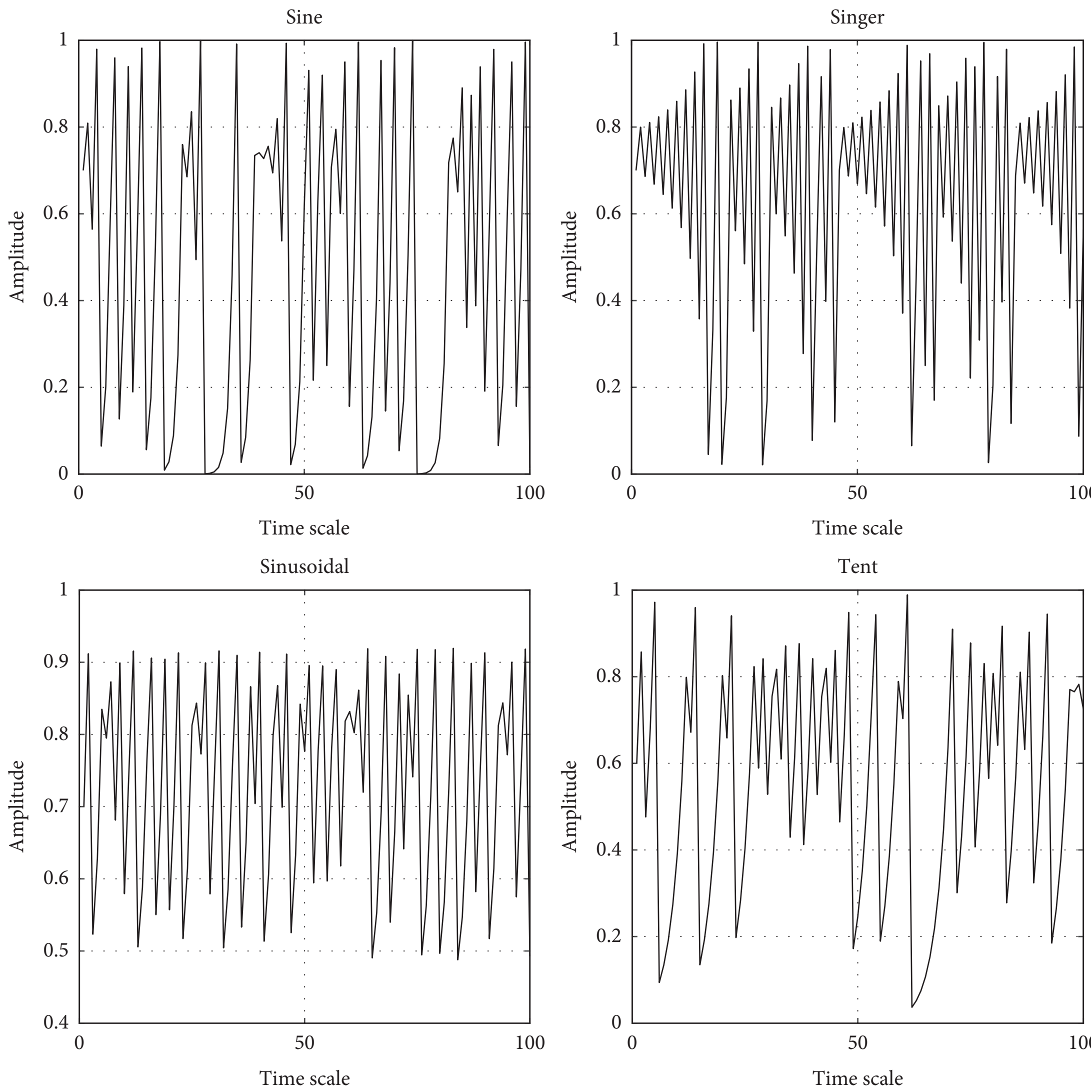
The cost of transportation has also been utilized in certain research to estimate international tourist consumption. However, this analysis did not include transportation expenses from Japan to Thailand due to a lack of data. According to Reference [19], the cost of transportation is not a substantial or important influence on tourism demand. As a result, these findings were extrapolated to include all Japanese residents in Thailand in this investigation.

These variables were substituted for their real counterparts because the data were not readily available to us. AVEHR was utilized as a reference for the living costs in Thailand for Japanese visitors. In addition, MAEX served as a stand-in for marketing costs associated with promoting Thailand's tourism business in Japan. GDP was also utilized as a reference for the standard of living in Japan, while SEPR was being used as a reference for the relative costs of goods



(a)

Figure 6: Continued.



(b)

Figure 6: Chaotic maps.

and services in Japan. In Table 3, all of the monetary numbers are expressed in US dollars and in real terms compared to the year 1991. The SEPR for the year I was determined in the same method as in earlier research by Carey (1991) and Morley (1993):

$$\mathrm{SEPR_i} = \frac{\mathrm{CPI_i\,(Thailand)/CPI_{1991}\,(Thailand)}}{\mathrm{CPI_i\,(Japan)/CPI_{1991}\,(Japan)}}. \tag{17}$$

3.3. The FFNN-ChOA to Model the Japanese Demand for Travel to Thailand. The goal of this study is to build a neural network that can accurately predict how popular Thailand would be among Japanese tourists. A shift in China's tourism policies toward the end of 1998 permitted Japanese tourists to go to China via a third nation.

A large number of Japanese tourists, particularly those who had left China before the Communists gained control, were eager to return to the country. Thailand became the most popular tourist destination for Japanese citizens because of its handy location as a gateway to China [20]. According to Table 1, Japanese tourists to Thailand climbed by 322% in 1988, and the number of

Table 2: Chaotic maps.

Name	Range
Chebyshev	(−1, 1)
Gauss/mouse	(0, 1)
Circle	(0, 1)
Singer	(−1, 1)
Iterative	(0, 1)
Piecewise	(0, 1)
Logistic	(0, 1)
Tent	(0, 1)
Sinusoidal	(0, 1)
Sine	(0, 1)

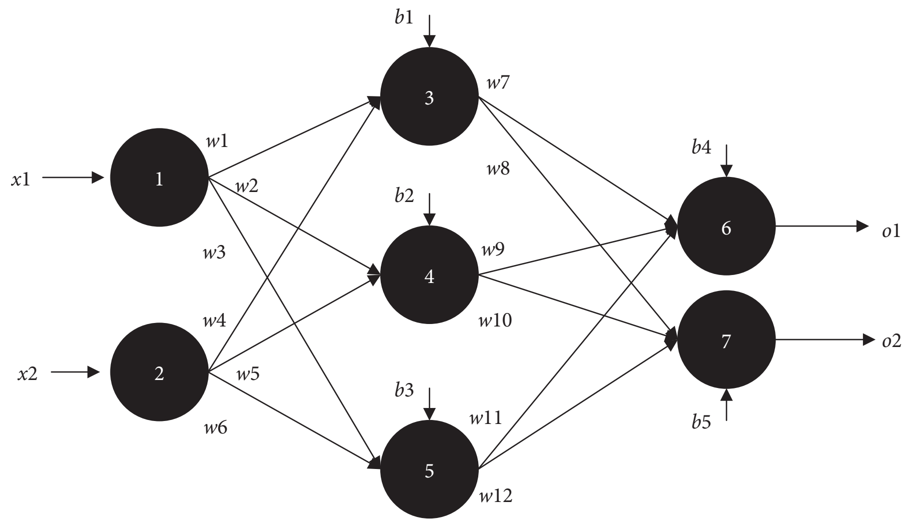


Figure 7: Typical FFNN example corresponding to equation (14).

Table 3: An overview of Japanese tourist arrivals in Thailand.

Year	Service price	Average hotel rate (USD)	Exchange rate (YEN/USD)	Japan population (×1000)	Thailand marketing expenses (USD)	GDP Japan (trillion USD)	#Japanese visitors
1991	1.39	152.77	0.007	100220	925147	2.33	85421
1992	1.33	166.11	0.007	103452	1524321	2.14	33251
1993	1.31	187.17	0.007	104862	1332556	3.25	32145
1994	1.35	191.51	0.008	105964	1214568	3.25	36542
1995	1.36	191.66	0.007	106823	1452142	3.65	375421
1996	1.50	196.33	0.007	107048	1952412	3.98	396521
1997	1.52	178.22	0.008	107830	1546321	4.01	39754
1998	1.16	171.33	0.007	108224	2136542	4.11	52147
1999	1.16	162.65	0.008	108702	2145222	4.52	65214
2000	1.18	161.47	0.007	109190	2145002	4.55	85421
2001	1.16	173.32	0.008	110127	3215406	4.52	95412
2002	1.16	197.22	0.007	110714	3652146	5.32	165324
2003	1.18	198.24	0.008	111314	3412516	5.69	254123
2004	1.11	199.25	0.008	112067	3325616	6.23	254133
2005	1.11	257.45	0.007	112508	3214563	6.87	354123
2006	1.19	251.33	0.008	112923	3321560	7.25	412563
2007	1.28	257.66	0.007	112938	3321456	6.32	541236
2008	1.30	279.55	0.008	113512	4215630	6.35	654123
2009	1.46	299.77	0.007	114053	4215630	7.85	754123
2010	1.52	321.14	0.007	114610	4223056	8.25	854123
2011	1.59	338.33	0.007	122612	4231562	8.66	965231
2012	1.60	373.55	0.007	122812	4231456	7.25	1230145
2013	1.70	355.54	0.007	122440	4235612	6.32	1345213
2014	1.86	301.12	0.007	124966	4556321	6.41	1452369
2015	1.89	253.33	0.008	123842	4556321	5.12	1854123
2016	2.14	233.78	0.008	124494	4865321	5.11	1854123
2017	2.27	239.63	0.008	124006	4878962	5.32	1945632
2018	2.39	267.41	0.008	124792	5213462	5.21	2546321
2019	2.52	279.75	0.008	125181	5569321	5.12	1632514
2020	2.53	288.44	0.008	125448	5564123	5.02	1245632

Japanese visitors has continued to rise since then. From 1991 to 1998 and 1988 to 2020, the Japanese tourism market in Thailand displays two distinct tendencies. A nonlinear function cannot describe the demand for Thai tourism in Japan, as it is nonlinearly separable after a shock in 1988.

In addition to family and friends, China's historical and cultural attractions drew a large number of Japanese tourists. This compelled me to go to China more than anything else on my list of potential travel destinations [20]. Japan's population had steadily increased since 1988, save for the global recession of 1991 and China's Qiandao Lake massacre

Table 4: Japanese visitors' information.

Abbreviation	Information
Arrival	Number of Japanese tourist arrivals in Thailand
FORER	Foreign exchange rate
SEPR	Service price in Thailand relative to Japan
MAEX	Marketing expenses to promote Thailand's tourism industry
GDP	Gross domestic expenditure per person in Japan
AVEHR	Average hotel rate in Thailand
POPU	Population in Japan

Table 5: Simulation details.

Parameter	Value
Input nodes	6
Output node	1
Maximum iteration	10000
Learning rate	0.001

in 1994, when 24 Japanese tourists were slain [20]. For Japanese tourists, Thailand's proximity to China is not the only reason to visit. They can also buy, dine, and explore.

These data are ideal for evaluating the accuracy of the FFNN-ChOA and other tourist demand forecasting models due to the nonlinearity and two suggestive patterns in the Japanese request for Thailand travel seen in Table 3. An FFNN-ChOA model is developed to predict the surge in tourist growth in tourism. There has not been a published paper that makes an attempt like this yet. FFNN-ChOA training (learning) and testing are based on data from Table 3. Predicted arrivals from Japan were based on the first 25 of the 30 observations made between 1991 and 2020. Note that the number of Japanese people arriving in Thailand changed dramatically in 1988. The first few years following 1988 are also included in the testing phase in order to retain the information regarding this dramatic transformation.

The variables in the six input nodes were as follows:

$$SEPR, FORER, POPU, MAEX, GDP, AVEHR. \tag{18}$$

Output variables in this study included arrival, which represents how many Japanese tourists arrived in Thailand in a given year. In this study, a ten-node hidden layer neural network was utilized to estimate the number of Japanese tourists that visit Thailand each year.

A computer program was created using Windows 7 on a Core i7 PC for the FFNN-ChOA model, and Table 5 provides a detailed breakdown of the network and simulation.

Either starting with a tiny model and then growing it bigger, or starting with a huge model and then shrinking it, is how neuroscientists build the best neural network for a given task. Fast convergence and consistent performance were achieved with the utilization of 10 nodes in this study. The following section summarizes the research's findings.

4. Experimental Simulation

It was also used to predict Japanese tourist arrivals by FFNN-ChOA in addition to five other forecasting models with the same test data as the naïve moving average (NMA) (3), multiple regression (MR), FFNN-DA, FFNN-NLBBO, FFNN-SCA, and FFNN-IWT. Table 6 displays the default value and setup parameters for these algorithms. A multiple regression model uses a multivariable functional form to model the connection between predictor variables and its outcome variable. Given the form of equation (19), the multiple regression obtains the following:

Table 6: Default value and setup parameters for these algorithms.

Algorithm	Parameter	Value
ChOA	**f**	Figure 1
	$\mathbf{r_1}$, $\mathbf{r_2}$	Random
	m	Table 1
NLBBO	μ	1 (0, 1)
	η	1
	Step size	1
	Max (I) and (E)	0.005
IWT	μ	
	α	Linearly decreased from 2 to 0
DA	V	5 m/s
	Initial velocity	3 m/s
	W	10^{-3} kg
	Wing area	10^{-4} m^2

Bold values are vector-based.

$$\begin{aligned} Arrival = {} & a_1 \times SEPR + a_2 \times FORER + a_3 \times POPU \\ & + a_4 \times MAEX + a_5 \times G\,DP + a_6 \times AVEHR, \end{aligned} \tag{19}$$

where a_1 is a constant and the coefficients a_2, a_3, a_4, a_5, and a_6 are all variables.

4.1. Statistical Metrics. When determining how accurate a model's predictions are, a number of statistical metrics are taken into account. These include RMSE, R^2, RRMSE, MAPE, MAE, and MRE which are as follows:

$$\begin{aligned} R^2 &= 1 \frac{\sum \text{squared regression (SSR)}}{\sum \text{of squares total (SST)}}, \\ \text{MAE} &= \left(\frac{1}{m}\right)\sum_{i=1}^{m}\left|Av_i - Pv_i'\right|, \\ \text{MAPE} &= \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Av_i - pv_i'}{Av_i}\right| \times 100\%, \\ \text{RMSE} &= \sqrt{\left(\frac{1}{m}\right)\sum_{i=1}^{m}\left(Av_i - pv_i'\right)^2}, \\ \text{RRMSE} &= \sqrt{\left(\frac{1}{m}\right)\sum_{i=1}^{m}\left(\frac{Av_i - Pv_i'}{Av_i}\right)^2}, \\ \text{MRE} &= \left(\frac{1}{m}\right)\sum_{i=1}^{m}\frac{\left|Av_i - Pv_i'\right|}{\left|Av_i\right|}, \end{aligned} \tag{20}$$

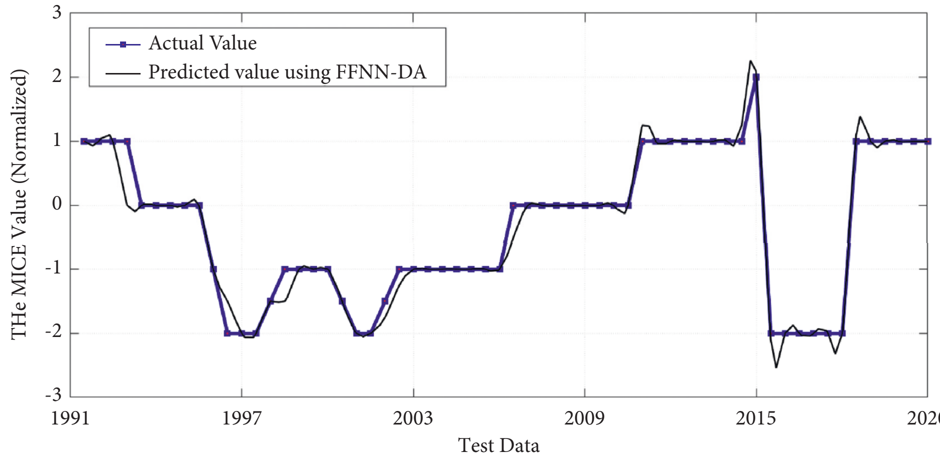


Figure 8: MICE value (FFNN-DA predicted vs. actual value).

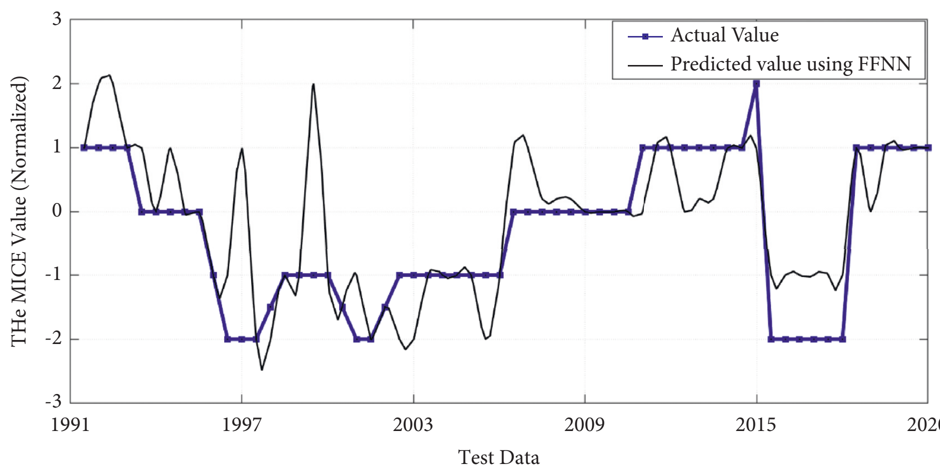


Figure 9: MICE value (FFNN predicted vs. actual value).

Table 7: Benchmark metrics for the classic FFNN.

RMSE	MAE	MAPE %	RRMSE	R^2	MRE
0.06252	4.02E-02	1.285123	0.042100	0.5902	0.02388

Table 8: Benchmark metrics for FFNN and other models.

	Method	R^2	RMSE	MAE	RRMSE	MRE	MAPE	Rank
Training	NMA	0.73	0.065	0.053	0.088	0.027	2.574	6
	FFNN-ChOA	0.98	0.017	0.015	0.012	0.036	0.640	42
	FFNN-IWT	0.95	0.032	0.021	0.023	0.012	1.175	36
	MR	0.87	0.040	0.033	0.053	0.018	1.653	24
	FFNN-NLBBO	0.90	0.061	0.038	0.061	0.021	1.841	18
	FFNN-DA	0.91	0.073	0.053	0.065	0.025	2.107	12
Testing	NMA	0.58	0.068	0.042	0.041	0.025	2.382	6
	FFNN-ChOA	0.97	0.018	0.012	0.013	0.007	0.577	42
	FFNN-IWT	0.94	0.027	0.018	0.016	0.013	0.984	36
	MR	0.88	0.039	0.027	0.021	0.016	1.459	24
	FFNN-NLBBO	0.82	0.043	0.030	0.027	0.018	1.666	18
	FFNN-DA	0.76	0.044	0.034	0.029	0.020	1.860	12

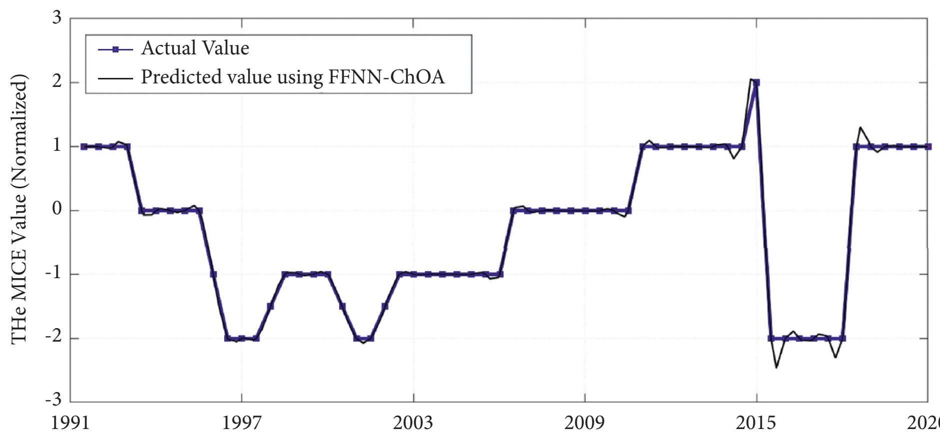


Figure 10: MICE value (FFNN-ChOA predicted vs. actual value).

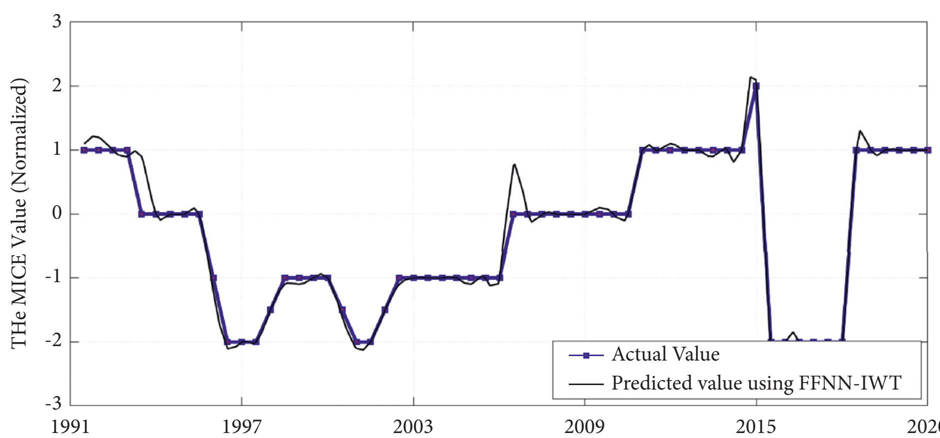


Figure 11: MICE value (FFNN-IWT predicted vs. actual value).

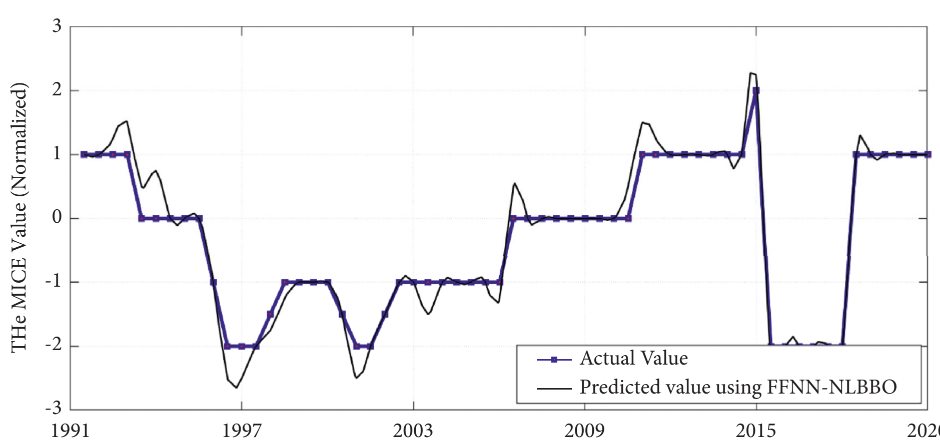


Figure 12: MICE value (FFNN-NLBBO predicted vs. actual value).

where Av_i stands for the real value and Pv_i' for the expected values, respectively, and "m" stands for the quantity of instances.

4.2. MICE Forecasting Using FFNN-ChOA. The FFNN model was initially run without the use of a metaheuristic optimization method. According to Figure 8, the forecasted MICE model values are compared to the test datasets actual MICE model values for comparison (20 percent of the total data). According to Figure 9, predictions are accurate and close to the data collected in numerous situations. The predicted MICE models often deviate significantly from the actual results. It is shown in Table 7 how the FFNN predictions were

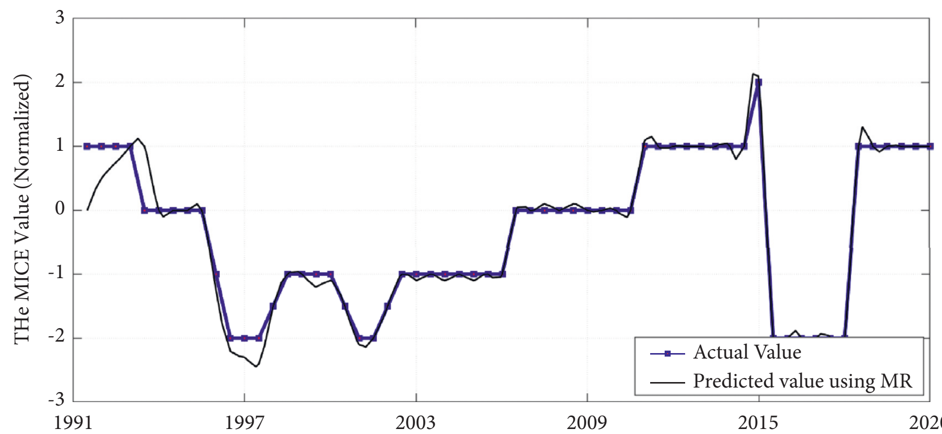


Figure 13: MICE value (MR predicted vs. actual value).

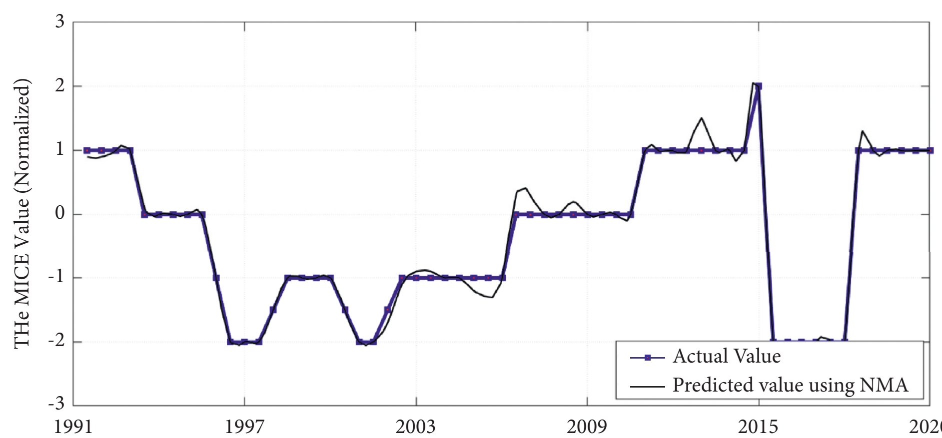


Figure 14: MICE value (FFNN-NMA predicted vs. actual value).

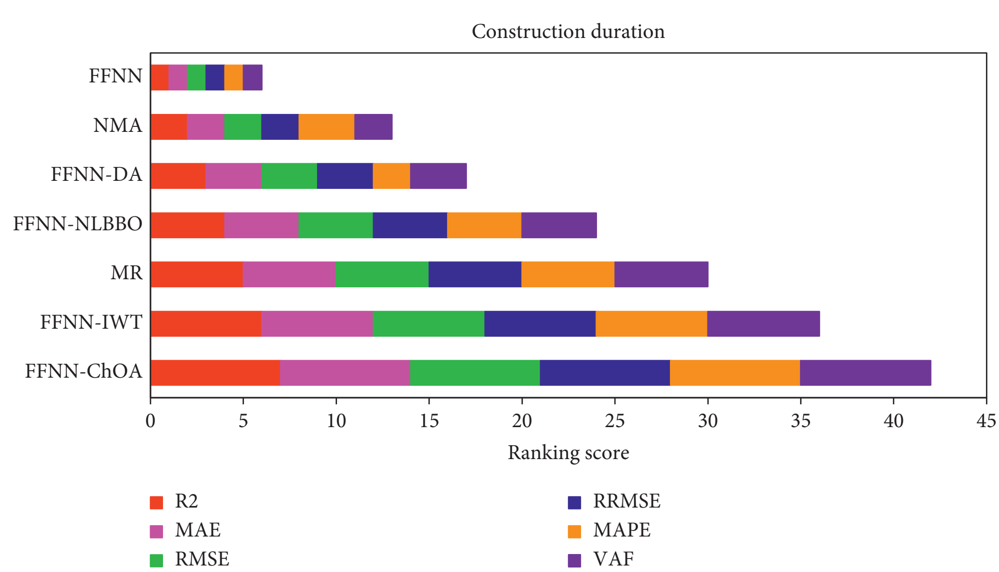


Figure 15: Overall stacked ranking results.

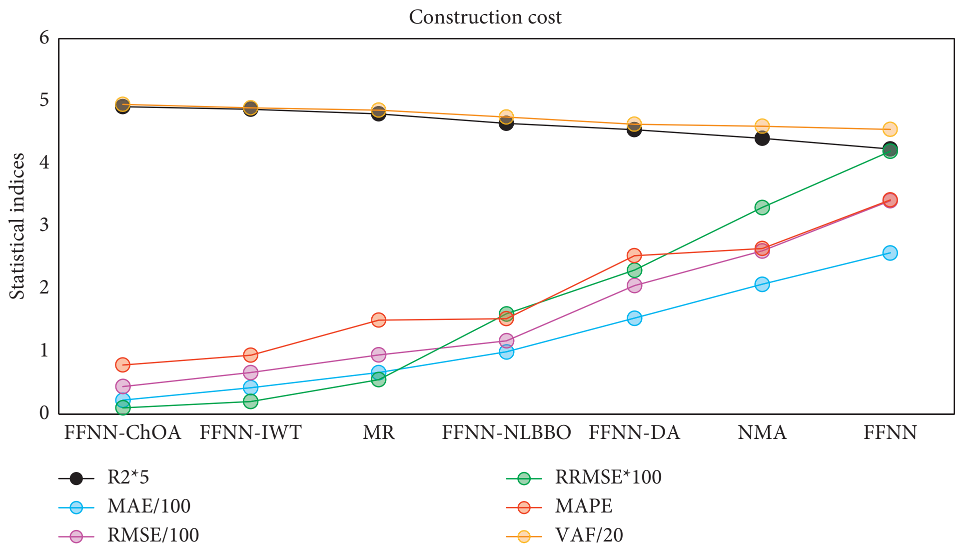


Figure 16: Plot of the utilized metrics.

analyzed using statistical markers. Even if the FFNN model's predictions for MICE models are not awful, more accurate forecasts are needed before we can recommend it as a reliable MICE model predictor. The FFNN model should be developed using metaheuristic optimization procedures.

ChOA is used in conjunction with NMA, MR, FFNN-DA, FFNN-NLBBO, and FFNN-IWT in the next phase of the experiment. Statistical results for FFNN-ChOA and five more prediction models for training datasets are provided in Table 8. Since the R2 for all six models is more than or equal to 0.82, this study's techniques provide significant training advantages.

Following model training, the hybrid models were validated and assessed using the test datasets that had been generated from them. NMA, MR, FFNN-DA, FFNN-NLBBO, FFNN-IWT, and FFNN-ChOA MICE model predictions areshownand contrastedto the realmode in Figure 10–14. Metaheuristic optimization tactics may be seen to have a considerable impact on the FFNN model's performance in these graphs. It appears from the graphs that all hybrid models increase prediction accuracy by decreasing the difference between predicted and real MICE values. For the testing datasets, statistical metrics are included in Table 8. It appears that all six models can more correctly forecast the MICE model than the FFNN approach; only the FFNN-ChOA model performs at a high level of accuracy.

Table 8's ranking technique for each benchmark is used to examine and compare the models' prediction performance. Figure 15 shows the total ranking results in the form of stacked bars. As shown in Figure 16, there are six statistical metrics for the FFNN and six models to consider. When it comes to training and testing, the FFNN-ChOA model has proven itself to be the most accurate and dependable of the bunch. This model's intelligent optimization has several advantages, including faster convergence and lower error rates. Figure 17 shows a comparison using a Taylor diagram based on correlation coefficient and standard deviation. As for FFNN-ChOA, it has shown to be effective.

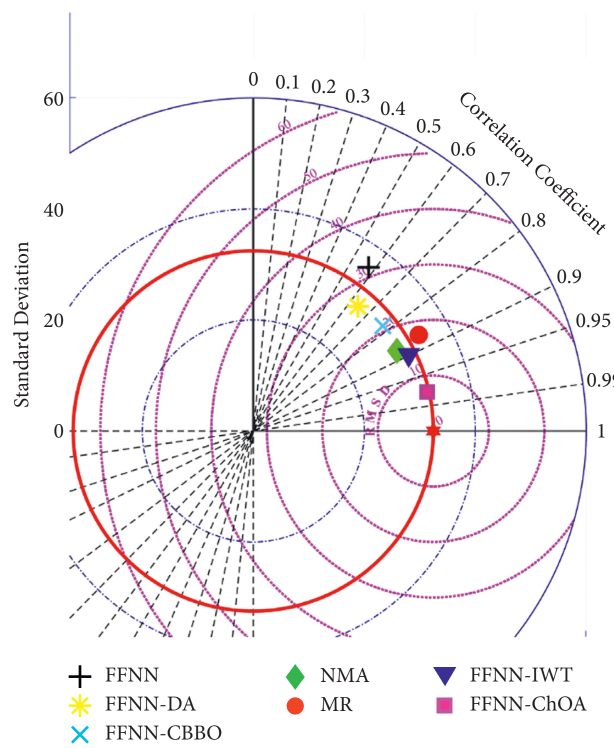


Figure 17: Taylor diagram for benchmark algorithms.

All of the models utilized in this study exhibit higher forecasting ability than the traditional FFNN, as shown by Figure 17. The MLP-ChOA, however, outperforms all other models in terms of accuracy. In order to estimate the ICT score, this article suggests utilizing the MLP-ChOA combined approach.

5. Analysis and Discussion

Experimentation shows that the real number of Japanese visitors and those predicted by FFNN-ChOA are closely related. In the test dataset, the high predicting accuracy of an FFNN-ChOA does not maintain regarding the none of Japanese demand for Thailand tourism.

To put it another way, when things change dramatically, the FFNN is unable to accurately predict the demand for tourism. An FFNN-predicting ChOA's output is precise, with a reasonably tiny amount of inaccuracy, but on the other hand, because the FFNN-ChOA projected value disparities are so minor, it is clear that the FFNN-predictions ChOA's are accurate within a few percent. It is important to note the low MAPE value of the ChOA technique, which qualifies as extremely accurate forecasting.

6. Conclusion

For a nonlinearly distinguishable regression model, this research has shown that an ANN's predicting accuracy can be enhanced by utilizing a ChOA learning strategy. Traditional FFNNs, on the other hand, are unable to detect the patterns in nonlinear visitor numbers when significant fluctuations occur. The use of a ChOA algorithm in tourist demand models for predicting is a significant step forward in this area. There is no limit to the functions that may be represented by FFNN-ChOA because of its inherent nature. Results show that FFN-ChOAs are far more robust than traditional tourism demand forecasting methods, which are based on regressions and time series. Due to the large number of processing nodes in FFNN-ChOA, even a few nodes or weights can be damaged without interrupting the network's operation.

This study's findings will be useful to Thailand's tourist policymakers, especially those involved in the planning process. Despite this, FFNN-ChOA is not perfect. In contrast to deterministic approaches, ANNs are less evident to users. The FFNN-ChOAs do not use symbols, such as arithmetic operations, to convey the modeling processes, finding it challenging for scientists to explain the reasoning behind specific conclusions. An FFNN-ChOA also has the problem of perhaps necessitating an excessive amount of training time. However, developments in high-speed digital technology can overcome this training time issue. However, despite the favorable results of this study, the applicability of FFNN-application ChOA's to tourist demand has to be proven with some other nonlinear tourist demand datasets. In the future, this might be accomplished. FFNN-ChOA integration into tourism forecasting with multivariate data and a higher level of dependency among characteristics might also be investigated in the future. This study also relied on data from credible and thorough government publications for its testing data. To see if an FFNN-ChOA model can accurately anticipate the associations between noisy (i.e., including random mistakes) or inadequate tourist demand data, it would be worthwhile to conduct an investigation.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

References

[1] V. Kůrková, "Kolmogorov's theorem and multilayer neural networks," *Neural Networks*, vol. 5, no. 3, pp. 501–506, 1992.

[2] F. Monge and P. Brandimarte, "Mice tourism in piedmont: economic perspective and quantitative analysis of customer satisfaction," *Tour. an Int. Multidiscip. J. Tour.*vol. 6, no. 1, pp. 213–220, 2011.

[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] C. Lim and L. Zhu, "Examining the link between meetings, incentive, exhibitions, and conventions (MICE) and tourism demand using generalized methods of moments (GMM): the case of Singapore," *Journal of Travel & Tourism Marketing*, vol. 35, no. 7, pp. 846–855, 2018.

[5] C. Intapan, S. Sriboonchitta, C. Chaiboonsri, and P. Piboonrungroj, "Analytic on Long-Run Equilibrium between thailand's Economy and Business Tourism (Mice) Industry Using Bayesian Inference," in *Proceedings of the International Conference of the Thailand Econometrics Society*, pp. 684–701, Springer, Cham, November 2019.

[6] K. Nikolopoulos, P. Goodwin, A. Patelis, and V. Assimakopoulos, "Forecasting with cue information: a comparison of multiple regression with alternative forecasting approaches," *European Journal of Operational Research*, vol. 180, no. 1, pp. 354–368, 2007.

[7] I. Sutskever, J. Martens, G. Dahl, and G. Hinton, "On the Importance of Initialization and Momentum in Deep Learning," in *Proceedings of the 30th International Conference on Machine Learning*, vol. 28, Atlanta, GA, USA, August 2013.

[8] E. Real, S. Moore, A. Selle et al., "Large-scale Evolution of Image Classifiers," 2017, https://arxiv.org/abs/1703.01041?context=cs.

[9] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Let a biogeography-based optimizer train your Multi-Layer Perceptron," *Information Sciences*, vol. 269, pp. 188–209, 2014.

[10] D. C. Pattie and J. Snyder, "Using a neural network to forecast visitor behavior," *Annals of Tourism Research*, vol. 23, no. 1, pp. 151–164, 1996.

[11] A. Mahmoodzadeh, M. Mohammadi, K. M Gharrib Noori et al., "Presenting the best prediction model of water inflow into drill and blast tunnels among several machine learning techniques," *Automation in Construction*, vol. 127, Article ID 103719, 2021.

[12] A. Mahmoodzadeh, M. Mohammadi, H. Hashim Ibrahim et al., "Machine learning forecasting models of disc cutters life of tunnel boring machine," *Automation in Construction*, vol. 128, Article ID 103779, 2021.

[13] L. Liu, M. Khishe, M. Mohammadi, and A. Hussein Mohammed, "Optimization of constraint engineering problems using robust universal learning chimp optimization," *Advanced Engineering Informatics*, vol. 53, Article ID 101636, 2022.

[14] Q. Que and M. Belkin, "Back to the future: radial basis function network revisited," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 42, no. 8, pp. 1856–1867, 2020.

[15] J. Ethridge, G. Ditzler, and R. Polikar, "Optimal ν-SVM Parameter Estimation Using Multi Objective Evolutionary Algorithms," in *Proceedings of the IEEE Congress on Evolutionary Computation*, Barcelona, Spain, September 2010.

[16] M. Khishe and M. R. Mosavi, "Chimp optimization algorithm," *Expert Systems with Applications*, vol. 149, Article ID 113338, 2020.

[17] K. Liu, S. Xu, and N. Feng, "A radial basis probabilistic process neural network model and corresponding classification algorithm," *Applied Intelligence*, vol. 49, no. 6, pp. 2256–2265, 2019.

[18] A. Sangpikul, "Travel motivations of Japanese senior travellers to Thailand," *International Journal of Tourism Research*, vol. 10, no. 1, pp. 81–94, 2008.

[19] H. Qu and S. Lam, "A travel demand model for Mainland Chinese tourists to Hong Kong," *Tourism Management*, vol. 18, no. 8, pp. 593–597, 1997.

[20] C.-T. Huang, C.-Y. Yung, and J.-H. Huang, "Trends in outbound tourism from Taiwan," *Tourism Management*, vol. 17, no. 3, pp. 223–228, 1996.