TOURISM DEMAND FORECASTING MODEL USING NEURAL NETWORK

Han-Chen Huang and Cheng-I Hou

Department of Tourism and M.I.C.E., Chung Hua University, Taiwan

ABSTRACT

Travel agencies should be able to judge the market demand for tourism to develop sales plans accordingly. However, many travel agencies lack the ability to judge the market demand for tourism, and thus make risky business decisions. Based on the above, this study applied the Artificial Neural Network combined with the Genetic Algorithm (GA) to establish a prediction model of air ticket sales revenue. GA was used to determine the optimum number of input and hidden nodes of a feedforward neural network. The empirical results suggested that the mean absolute relative error (MARE) of the proposed hybrid model’s predicted value of air ticket sales revenue and the actual value was 10.51% and the correlation coefficient was 0.913. The proposed model had good predictive capability and could provide travel agency operators with reliable and highly efficient analysis data.

KEYWORDS

Artificial neural network; Genetic algorithm; Air ticket sales; Prediction model

1. INTRODUCTION

There are nearly 3,500 travel agencies competing in the overseas tourism market in Taiwan, with a value of about USD21 billion per year [1]. In a competitive environment, travel agencies must be able to accurately predict the market demand to make the right operational decisions. However, tourism is not an essential component of people’s lives, and tourism can be directly affected by economic downturns. Travel agency operators should have good predictive capability for market demand and excellent financial management capability; otherwise, it will be difficult to survive in a competitive market [2].

Among the numerous businesses of travel agencies, air ticket sales are an extremely important source of revenue. If a travel agency can accurately predict the market demand for air tickets, it can purchase a sufficient amount of air tickets at a low cost to have the opportunity to get higher sales profits. In addition, it can reduce the cost accumulation during the purchase process or order loss due to lack of air tickets [3,4].

Studies in the past have developed many sales prediction models, such as qualitative methods (the Delphi method, market research, and the group opinion method), the sequence analysis method (exponential smoothing, autoregressive models, moving average models, etc.) and econometric methods (discussing the relationship with external economic variables and using statistical theoretical method to measure or test the relationships in between some variables to provide the basis for analysis). However, these models have a number of limitations [5]. In recent years, the prevalent prediction method has been artificial intelligence. Among the various types of artificial intelligence prediction models, neural networks have been confirmed as a very effective tool [6]. Therefore, this study applied an Artificial Neural Network (ANN) combined with the Genetic Algorithm (GA) to establish a prediction model for air ticket sales revenue. The findings of this study could provide the industry with a more reliable and efficient reference in practical operation.
2. LITERATURE REVIEW

2.1. Travel Agencies

Travel agencies are the mediators of tourism product suppliers and customers, as they are responsible for planning and making arrangements for tours in order to win profits[2]. In accordance with Taiwan’s Statute for the Development of Tourism[7] Article 2 states that a travel enterprise is: “also referred to as travel agency, a profit-taking enterprise licensed by the central administrative authority to provide tourists with arranged travel schedules, board and lodging, tour guides, and to purchase transportation tickets and apply for travel documents and visas on tourists’ behalf, as well as to provide related services for remuneration.”

There are nearly 3,500 travel agencies competing in the overseas tourism market in Taiwan, with a value of about USD21 billion per year[1]. In such a competitive environment, travel agencies must be able to more efficiently and accurately predict market demand to make the right operational decisions. If a travel agency can understand the market demand earlier than its competitors, purchase products, mobilize manpower and adjust business operational directions in advance, it can surely win in a fiercely competitive environment.

2.2. Prediction Methods

Stynes[8] categorized prediction methods into four types: 1) the Delphi technique; 2) time series or trend extension models; 3) structural models; and 4) system or simulation models. The commonly used prediction methods proposed in other related studies [9-16] include trend analysis, cause analysis, judgment analysis, survey analysis, and artificial neural networks, etc.

2.2.1. Trend Analysis

The trend analysis method is used to predict the trend changes in future sales of an enterprise according to the historical sales data by using certain calculation methods. Such a method is suitable for enterprises with relatively stable product sales. It mainly includes the simple moving average method, the moving average method, the weighted moving average method, the exponential smoothing method and the seasonal prediction method.

2.2.2. Cause Analysis

Various factors in economic activities are often interrelated, mutually influential, and form a certain corresponding relationship among each other. Product sales in general are affected by various factors. The cause analysis method is used to find the function relationship of various related factors that may affect product sales and sales volume, as well as to predict future sales according to such a causality relationship. Such a method often requires the establishment of prediction mathematical model, and thus it is often known as the regression analysis method. It commonly includes simple regression analysis and multiple regression analysis.

2.2.3. Judgment Analysis

As a qualitative analysis method, judgment analysis is mainly based on the analysis of future market changes according to the experience of management personnel, personnel with sales experience, or other experts, in order to determine the sales trends of certain products in a certain period of time.
2.2.4. Survey Analysis

The survey analysis method is used to predict the sales trends of the product of an enterprise by investigating the demand and supply of a certain product and the consumption orientation of consumers. The survey contents may include product surveys, customer surveys, surveys on economic development trends and industry surveys, etc.

2.2.5. Artificial Neural Network

An artificial neural network (ANN) is a mathematical model imitating the structure and function of a biological neural network. The neural network performs calculations using a large amount of artificial neurons. In most cases, ANN can change the internal structure according to external information as an adaptive system. ANNs are a modeling tool for non-linear statistical data, and they are commonly used for the modeling of complex relationships between input and output or data exploration [17].

ANN construction is generated by the inspiration of biological neural networks. ANN can have human-like simple determination capability and judgment, which is advantageous to formal logic reasoning. A common multilayer feedforward network consists of three parts (Figure 1)[18-20]:

- The input layer, in which numerous neurons receive a large amount of input information.
- The output layer, in which information is transmitted and analyzed in neuron links to form the output results.
- The hidden layer, which is a layer with numerous neurons and links in between the input and the output layers. It can consist of multiple layers but is customarily one layer only. There is no recognized number of neurons in the hidden layer; however, when the number of neurons is larger, the non-linearity will be more significant and the robustness of the neural network will be more significant.

![Figure 1. BPNN network architecture][18-20]

The Back Propagation Neural Network (BPNN) is the most representative and commonly used ANN[18]. BPNN applies the steepest descent method to adjust the parameters of the network and
obtain a more accurate solution by iteration computation. BPNN has high-speed computing power, a fast recall speed, high learning accuracy, and fault tolerance, and thus it has been widely applied in different fields[18-20].

3. RESEARCH METHOD

3.1. Back Propagation Neural Network

BPNN is a supervised learning algorithm consisting of ANNs. A BPNN is the combination of multilayer perceptrons (MLP) and error back propagation (EBP). The computation process can be divided into the learning process and the recall process[21].

3.1.1. Learning process

Step1: Set the network architecture parameters and learning parameters
Step2: Randomly generate the weight matrix and bias vector initial value
Step 3: Input the training examples, including the input values (X\textsubscript{1},X\textsubscript{2},X\textsubscript{3}) and target output values (T\textsubscript{1},T\textsubscript{2},T\textsubscript{3})
Step4: Compute and infer the output values (Y\textsubscript{1},Y\textsubscript{2},Y\textsubscript{3})

(1) Hidden layer (H\textsubscript{1},H\textsubscript{2},H\textsubscript{3})(Eq.1 and 2)

\[ \text{net}_k = \sum_i W_{ik} x_i - \theta_k \]  
\[ H_k = \frac{1}{1 + \exp(-\text{net}_k)} \]  

(2) Output layer (Y\textsubscript{1},Y\textsubscript{2},Y\textsubscript{3}) (Eq.3 and 4)

\[ \text{net}_j = \sum_i W_{ij} h_i - \theta_j \]  
\[ Y_j = \frac{1}{1 + \exp(-\text{net}_j)} \]  

Step5: Compute the gap \( \delta \)(Eq.5 and 6)

(1) Hidden layer
\[ \delta_k = \left( \sum_j \delta_j \cdot W_{jk} \right) \cdot h_k \cdot (1 - H_k) \]  

(2) Output layer
\[ \delta_j = (T_j - Y_j) \cdot Y_j \cdot (1 - Y_j) \]  

Step6: Compute weight revision and bias revision (Eq.7-10)

(1) Hidden layer
\[ \Delta W_{ik} (n) = \eta \delta_k x_i + \alpha \cdot \Delta W_{ik} (n-1) \]
\[
\Delta \theta_k(n) = -\eta \delta_k + \alpha \cdot \Delta \theta_k(n-1) \tag{8}
\]

(2) Output layer
\[
\Delta W_{kj}(n) = \eta \delta_j H_k + \alpha \cdot \Delta W_{kj}(n-1) \tag{9}
\]
\[
\Delta \theta_j(n) = -\eta \delta_j + \alpha \cdot \Delta \theta_j(n-1) \tag{10}
\]

Step 7: Update the weight and bias (Eq. 11~14)

(1) Hidden layer
\[
W_{jk} = W_{jk} + \Delta W_{jk} \tag{11}
\]
\[
\theta_k = \theta_k + \Delta \theta_k \tag{12}
\]

(2) Output layer
\[
W_{kj} = W_{kj} + \Delta W_{kj} \tag{13}
\]
\[
\theta_j = \theta_j + \Delta \theta_j \tag{14}
\]

Step 8: Repeat Step 3- Step 7 until convergence (no significant change in error or implementation of certain times of learning cycles).

3.1.2. Recall process

Step 1: Set network parameters
Step 2: Read in the weight matrix and bias vector
Step 3: Input the unknown data vector \(X_1, X_2, X_3\)
Step 4: Compute and infer the output vector \(y_1, y_2, y_3\)

(1) Hidden layer output values \(H_1, H_2, H_3\) (Eq. 15 and 16)
\[
net_k = \sum_i W_{ik} X_i - \theta_k \tag{15}
\]
\[
H_k = \frac{1}{1 + \exp(-net_k)} \tag{16}
\]

(2) Compute and infer the output values \(Y_1, Y_2, Y_3\) (Eq. 17 and 18)
\[
net_j = \sum_k W_{kj} H_k - \theta_j \tag{17}
\]
\[
Y_j = \frac{1}{1 + \exp(-net_j)} \tag{18}
\]

3.2. Forecast Model Variables

According to the relevant literature [13-16, 22-26], this study used the NTD/USD exchange rate, the number of people traveling abroad from Taiwan each month, the international oil price, the
Taiwan stock market weighted index, Taiwan’s monthly monitor indicator, Taiwan’s monthly composite leading index, Taiwan’s monthly composite coincident index, and W travel agency’s monthly air ticket sales (T-1 ~ T-18) (Table 1) as the input variables to predict W travel agency’s air ticket sales revenue in Month T. The selected data were the monthly data of the period from January 2003 to December 2015. This study randomly selected 70% as the training data, 15% as the cross validation data, and 15% as the testing data. GA improves the performance of ANNs by selecting the optimum input features of the neural network. This study used different operators for selection and crossover operations (Table 2)[26-30].

Table 1. Forecast model variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>NTD/USD exchange rate (T-1 month)</td>
<td>NTD/USD</td>
</tr>
<tr>
<td>Number of people traveling abroad from Taiwan each month (T-1 month)</td>
<td>Number of people</td>
</tr>
<tr>
<td>International oil price (T-1 month)</td>
<td>USD/Barrel</td>
</tr>
<tr>
<td>Taiwan stock market weighted index (T-1 month)</td>
<td>Point</td>
</tr>
<tr>
<td>Taiwan’s monthly monitor indicator (T-1 month)</td>
<td>Score</td>
</tr>
<tr>
<td>Taiwan’s monthly composite leading index (T-1 month)</td>
<td>Point</td>
</tr>
<tr>
<td>Taiwan’s monthly composite coincident index (T-1 month)</td>
<td>Point</td>
</tr>
<tr>
<td>W Travel Agency’s air ticket sales revenue (T-1 month to T-18 month)</td>
<td>NTD</td>
</tr>
</tbody>
</table>

Output

| Air ticket sales revenue (T month) | NTD |

Table 2. Description of different operators for select and crossover operations in GA[26-30]

<table>
<thead>
<tr>
<th>Operation</th>
<th>Operator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select</td>
<td>Best</td>
<td>Selects the best chromosome.</td>
</tr>
<tr>
<td></td>
<td>Random</td>
<td>Randomly selects a chromosome from the population.</td>
</tr>
<tr>
<td></td>
<td>Tournament</td>
<td>The winner of each tournament (the one with the best fitness) is selected for crossover.</td>
</tr>
<tr>
<td></td>
<td>Top percent (15)</td>
<td>Randomly selects a chromosome from the top 15 percent of the population.</td>
</tr>
<tr>
<td></td>
<td>Roulette</td>
<td>The chance of a chromosome getting selected is proportional to its fitness.</td>
</tr>
<tr>
<td>Crossover</td>
<td>Arithmetic</td>
<td>Linearly combines two parent chromosome vectors to produce two new offspring.</td>
</tr>
<tr>
<td></td>
<td>Heuristic</td>
<td>Use the fitness values of the two parent chromosomes to determine the direction of the search.</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>Decides (with some probability – known as the mixing ratio) which parent will contribute each of the gene values in the offspring chromosomes.</td>
</tr>
<tr>
<td></td>
<td>One point</td>
<td>Randomly selects a crossover point within a chromosome, interchanges the two parent chromosomes at this point to produce two new offspring.</td>
</tr>
<tr>
<td></td>
<td>Two point</td>
<td>Randomly selects two crossover points within a chromosome, interchanges the two parent chromosomes between these points to produce two new offspring.</td>
</tr>
</tbody>
</table>
3.3. Architecture Design and Model Training

ANN’s input activation function uses the hyperbolic tangent, the output error function uses the sum-of-squares and the output activation function uses logistic. GA improves the performance of ANNs by selecting the optimum hidden nodes of the neural network. This study used different operators for selection and crossover operations (Table 2)[26-30].

Training Algorithm: Quick Propagation Algorithm, Training Algorithm’s Parameters is Quick Propagation Coefficient = 1.75, Learning Rate=0.1. The overtraining control and weights randomization methods were used to increase the model accuracy (Figure 2).

4. **Empirical Results**

The correlation (r) and Mean Absolute Relative Error (MARE) were adopted as indicators for evaluating the model.

- **Correlation (r):** As r approaches 1, the model predicted value and actual value correlation level becomes higher.
- **MARE (Eq. 19):** The smaller the value, the smaller the error between the forecast value and the actual value:

  \[
  MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_i - Y_i'}{Y_i} \right| \times 100\% 
  \]  

  (19)

  where n is the number of the forecasting periods, \(Y_i\) is the actual value for the i period, and \(Y_i'\) is the forecast value for the i period.

The optimal network architecture is 12-142-1 (Figure 3 and Table 3). The input layer had 12 neurons, the hidden layer had 142 neurons, and the output layer had one neuron. The actual value and model output value distribution are shown in Figure 4. It can be learnt from the figure that the model output value was largely distributed along both sides of the diagonal line (Output/Target=1), indicating the model had good predictive capability. The trends of the actual value and model output value are shown in Figure 5. It can be learnt from the figure that the established air ticket sales revenue prediction model had a good capability to reflect the change in
sales of air tickets. The prediction results of the model are shown in Table 4. The mean absolute relative error (MARE) was 10.51%, the correlation coefficient was 0.913, and the model had the capability of accurately predicting the air ticket sales revenue.

![Figure 3. Best network architecture search results](image)

Table 3. Performance of the Proposed Model in Prediction

<table>
<thead>
<tr>
<th>Select operator</th>
<th>Crossover operator</th>
<th>Number of inputs</th>
<th>Number of hidden nodes</th>
<th>MARE</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Best</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arithmetic</td>
<td>10</td>
<td>24</td>
<td>0.1113</td>
<td>0.913</td>
<td></td>
</tr>
<tr>
<td>Heuristic</td>
<td>7</td>
<td>22</td>
<td>0.1301</td>
<td>0.876</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>11</td>
<td>53</td>
<td>0.1471</td>
<td>0.919</td>
<td></td>
</tr>
<tr>
<td>One point</td>
<td>9</td>
<td>90</td>
<td>0.1149</td>
<td>0.876</td>
<td></td>
</tr>
<tr>
<td>Two point</td>
<td>5</td>
<td>75</td>
<td>0.1281</td>
<td>0.900</td>
<td></td>
</tr>
<tr>
<td><strong>Random</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arithmetic</td>
<td>4</td>
<td>127</td>
<td>0.1215</td>
<td>0.916</td>
<td></td>
</tr>
<tr>
<td>Heuristic</td>
<td>7</td>
<td>86</td>
<td>0.1426</td>
<td>0.923</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>4</td>
<td>8</td>
<td>0.1457</td>
<td>0.928</td>
<td></td>
</tr>
<tr>
<td>One point</td>
<td>8</td>
<td>127</td>
<td>0.1270</td>
<td>0.898</td>
<td></td>
</tr>
<tr>
<td>Two point</td>
<td>7</td>
<td>142</td>
<td>0.1051</td>
<td>0.913</td>
<td></td>
</tr>
<tr>
<td><strong>Tournament</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arithmetic</td>
<td>5</td>
<td>54</td>
<td>0.1284</td>
<td>0.876</td>
<td></td>
</tr>
<tr>
<td>Heuristic</td>
<td>8</td>
<td>136</td>
<td>0.1337</td>
<td>0.890</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>13</td>
<td>149</td>
<td>0.1251</td>
<td>0.897</td>
<td></td>
</tr>
<tr>
<td>One point</td>
<td>13</td>
<td>34</td>
<td>0.1539</td>
<td>0.925</td>
<td></td>
</tr>
<tr>
<td>Two point</td>
<td>10</td>
<td>72</td>
<td>0.1607</td>
<td>0.936</td>
<td></td>
</tr>
<tr>
<td><strong>Top percent (15)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arithmetic</td>
<td>4</td>
<td>17</td>
<td>0.1406</td>
<td>0.920</td>
<td></td>
</tr>
<tr>
<td>Heuristic</td>
<td>9</td>
<td>20</td>
<td>0.1447</td>
<td>0.923</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>11</td>
<td>65</td>
<td>0.1296</td>
<td>0.923</td>
<td></td>
</tr>
<tr>
<td>One point</td>
<td>12</td>
<td>64</td>
<td>0.1647</td>
<td>0.915</td>
<td></td>
</tr>
<tr>
<td>Two point</td>
<td>7</td>
<td>24</td>
<td>0.1093</td>
<td>0.934</td>
<td></td>
</tr>
<tr>
<td><strong>Roulette</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arithmetic</td>
<td>4</td>
<td>23</td>
<td>0.1532</td>
<td>0.916</td>
<td></td>
</tr>
<tr>
<td>Heuristic</td>
<td>13</td>
<td>58</td>
<td>0.1421</td>
<td>0.878</td>
<td></td>
</tr>
<tr>
<td>Uniform</td>
<td>6</td>
<td>5</td>
<td>0.1136</td>
<td>0.875</td>
<td></td>
</tr>
<tr>
<td>One point</td>
<td>12</td>
<td>143</td>
<td>0.1211</td>
<td>0.918</td>
<td></td>
</tr>
<tr>
<td>Two point</td>
<td>5</td>
<td>104</td>
<td>0.1451</td>
<td>0.913</td>
<td></td>
</tr>
</tbody>
</table>
5. CONCLUSION

This study used the Back Propagation Neural Network and Genetic algorithm (GA) to establish a travel agency air ticket sales revenue prediction model. GA was used to determine the optimum number of input and hidden nodes of a feedforward neural network. The empirical results suggested that the proposed prediction model had the capability to accurately predict air ticket sales revenue and reflect the change in air ticket sales. The MARE of the model was only 10.51%, and the correlation coefficient was up to 0.913. When using the proposed prediction model, travel agency operators can predict the future demand for air tickets and purchase sufficient air tickets at a lower cost to win more profits. It could reduce the loss caused by excessive purchase or customer loss caused by lack of stock.
REFERENCES


