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ARTIFICIAL INTELLIGENC E TECHNOLOGY IN TRAVEL AGENCY OPERATING REVENUE FORECASTS

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ABSTRACT

The state of the economy has a great impact on the tourism industry; therefore, the management of a travel agency requires good financial revenue and expenditure management. Otherwise, travel agencies have difficulties surviving in a highly competitive market. Establishing an effective and accurate revenue forecasting model can enable travel agencies to predict possible financial crises, providing operators with time to react and adjust their management direction. This study used an artificial neural network (ANN) to establish an operating revenue forecasting model. According to the actual data verification results, the model presented in this study had 12.257% absolute relative error (ARE). This indicated that this model has an accurate forecasting ability and can provide reliable and efficient reference data for operators.

Keywords: *Travel Agency, Financial Revenue, Forecasting, Artificial Neural Network, Operating Revenue*

1. INTRODUCTION

Corporate financial management is a vital part of operating-revenue management, and relates to the survival and development of the business. Reinforcing operating-revenue management allows a business' various expenditures to have a reasonable return, and is suitable for use for production activities [1]. Furthermore, it can provide companies a more in-depth understanding of changing market demands, facilitating the formulation of appropriate business decisions.

Tourism is not a necessary expenditure; thus, when an economic downturn occurs, it affects the tourism industry directly. If a travel agency cannot make accurate forecasts of changing market demands, their financial revenue and expenditure management can face unaffordable risks [2]. Therefore, establishing an effective and accurate operating revenue-forecasting model is critical to travel agencies.

Accurately forecasting market demands can reduce cost pressure created by overstocking and lost orders because of shortages. Accurate stocking provides a travel agency with a competitive advantage and profit earnings [3]. To achieve this goal, this study used an Artificial Neural Network (ANN) to establish a travel-agency operating revenue-forecasting model. The study results can provide operators with a more accurate and efficient reference for actual operations.

2. LITERATURE REVIEW

Numerous methods are available for operating-revenue forecasting. The more commonly used methods include judgment analysis, survey analysis, trend analysis, causal analysis, and artificial intelligence [4, 5].

2.1 Judgment Analysis

This is a commonly used method of qualitative analysis. It uses the analysis of future market changes by experienced corporate management personnel, staff with extensive sales experience, or experts to judge the corporate sales trend of a product within a set period.

2.2 Survey Analysis

This type of forecast uses a commodity market supply and demand investigation and a consumer-spending orientation survey to forecast a corporation's product sales trend. Survey contents include a product survey, customer survey, economic development trend survey, and same industry survey.

2.3 Trend Analysis

Trend analysis uses a formula to forecast future sales trends based on corporate historical sales data. This method is suitable for product sales that are relatively stable and for corporations that have set sales changes. Trend analysis is a type of

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forecasting method that uses historical data for future predictions. The following are certain specific methods: the simple moving average, moving average, weighted moving average, exponential smoothing method, and seasonal forecasting method.

2.4 Causal Analysis

In economic activities various factors are often interrelated and influence each other, forming correlations. Product sales are generally always influenced by various factors. Causal analysis identifies functional relationships among factors that influence produce sales, and use these causal relationships to create a sales forecast. This method often requires establishing a mathematical forecasting model, using one of the following methods: regression analysis, simple regression analysis, or multiple regression analysis.

2.5 Artificial Intelligence

Artificial-intelligence forecasting models have recently replaced past forecasting models. Of the different artificial-intelligence forecasting models, the Back Propagation Neural Network (BPNN) has proven to be effective [6]. BPNN has high-speed computing power, fast recall speed, high learning accuracy and fault tolerance. It has been applied to numerous different fields. BPNN is the most representative and most used of the ANN models. BPNN architecture is a multilayer perceptrons (MLP) and uses a learning algorithm known as error back propagation (EBP) [7]. The MLP has a hidden layer between the input and output layers; the hidden layer can be one or more levels. A general BPNN architecture is shown below:

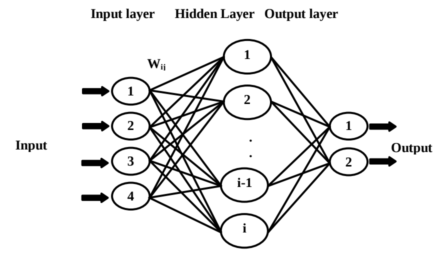

Figure 1: Network architecture

3. FORECASTING MODEL

3.1 Input variables

Using relevant literary contributions [8-16], this study used oil prices (West Texas Intermediate Oil, Brent Crude Oil, and Dubai Crude Oil), the Taiwan Weighted Stock Index (monthly closing values and the average value), the NTD/USD exchange rate, gold price, number of people traveling abroad from Taiwan each month, Taiwan's monthly unemployment rate, Taiwan's monthly unemployment number, Taiwan's monthly monitor indicator, Taiwan's monthly composite leading index, the Taiwan monthly composite coincident index, and 12 of W traveling agency's monthly operating revenue (T-1 month to T-12 month; Table 1) as the input variables for forecasting W travel agency's business performance. The data obtained was for January 2003 to October 2012. Random selection chose 68% as training data, 16% as the cross-validation data, and 16% as the testing data.

Table1: Forecast Model Variables

	Variables	Unit
Input	International oil price (T-1 month)	USD/barrel
	Taiwan stock market weighted index (T-1 month)	Point
	NTD/USD exchange rate (T-1 month)	NTD/USD
	Gold price (T-1 month)	USD
	People traveling abroad from Taiwan each month (T-1 month)	Number of people
	Taiwan's monthly unemployment number (T-1 month)	Thousand
	Taiwan's monthly unemployment rate (T-1 month)	%
	Taiwan's monthly monitor indicator (T-1 month)	Score
	Taiwan's monthly composite leading index (T-1 month)	Point
	Taiwan's monthly composite coincident index (T-1 month)	Point
	W Travel Agency's operating revenue (T-1 month to T-12 month)	NTD
Output	operating revenue (T month)	NTD

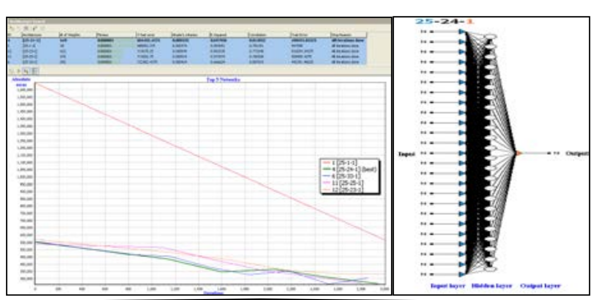

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Figure 2: Best Network Architecture Search Results

3.2 Architecture Design

The network input activation function uses the hyperbolic tangent, the output error function using Sum-Of-Squares, and output activation-function adopted logistics. The architecture design used Test Error and the evaluation standard for searching for the best network architecture (Fig. 2). The best network architecture is 25-24-1. The input layer counted 25 neurons. The hidden layer consisted of only one layer and 24 neurons, and the output layer had one neuron.

4. MODEL RESULTS

The training algorithm for BPNN training used quick propagation. The training algorithm's parameters were the quick propagation coefficient = 1.75 and learning rate = 0.1. The actual value and the model output value distribution is shown in Fig. 3. From this figure we can see that the model output values were mostly distributed on the two sides of the diagonal line (Output/Target= 1). This indicates that the model has good forecasting abilities. The actual values and model output value graph is shown in Fig. 4.

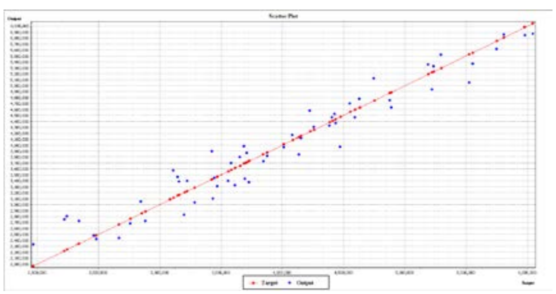

Figure 3: Scatter Plot Of Actual Value And Model Output Value

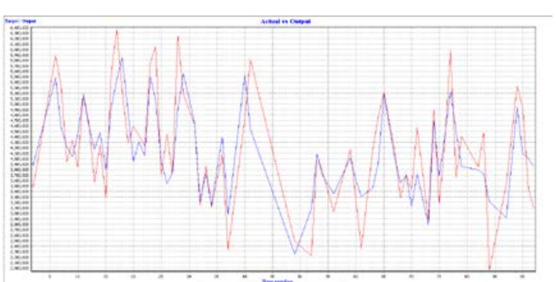

Figure 4: Actual Value And Model Output Value Graph

This figure shows that the operating revenue-forecasting model established by this study has the capability to reflect operating-revenue fluctuations. The model training results are shown in Table 2. The ARE is 9.2791%, indicating a low error. The correlation coefficient is 0.911013, indicating high relevance. This means that the training model can learn the training data to less than a 10% margin of error. The model testing results are shown in Table 3. The ARE is 12.257% and the correlation coefficient is 0.795325. This means that the forecasting model has the ability to accurately forecast the actual operating revenue.

Table 2: Model Training Results

	Target	Output	Absolute Error	Absolute Relative Error
Mean	3897306.41	3917252.46	322003.31	0.092791
Standard Deviation	996155.28	863021.33	259692.80	0.091807
Correlation: 0.911013				

Table 3: Model Forecast Results

	Target	Output	Absolute Error	Absolute Relative Error
Mean	4106892.83	3919198.62	498752.84	0.122570
Standard Deviation	1006322.89	882310.13	488699.95	0.112330
Correlation: 0.795325				

5. CONCLUSION

This study uses a BPNN to establish a travel agency's operating revenue forecasting model. Through the input of 25 variables, the model forecasted a travel agency's future operating revenue. Empirical result showed that the model has good forecasting abilities. The absolute relative error was only 12.257% and the correlation coefficient was 0.795325. The forecasting model has the ability to forecast actual operating revenue. If travel agencies are able to promptly forecast future operating income changes, they would be able to predict possible financial crises, allowing operators to promptly adjust and change their management direction.

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