APPLYING FUZZY REGRESSION FORECASTING MODEL TO PREDICT TAIWAN INTERNATIONAL AIR CARGO VOLUME

Chou, Tsung-Yu
Assistant Professor
Dept. of Distribution Management
National Chin-Yi University of Technology, 35, Lane215, Section 1, Chung-Shan Road, Taiping City, Taichung County, 411 Taiwan, R.O.C.
Tel: +886-4-2389-2088 ext:3552
E-mail: cjy920@ms49.hinet.net

Liang, Gin-Shuh
Professor
Dept. of Shipping and Transportation Management
National Taiwan Ocean University 2 Pei-Ning Rd., Keelung, Taiwan, R.O.C.
Fax: +886-2-2463-1903
E-mail: gsliang@mail.ntou.edu.tw

Han, Tzeu-Chen
Vice Professor
Dept. of Shipping and Transportation Management
National Penghu University 300, Liu-Ho Rd., Ma-kung, Penghu, Taiwan, R.O.C.
Fax: +886-6926-5760
E-mail: tchani@npu.edu.tw

Hsu, Chia-Lun
Lecturer
Department of International Business Management, Ling Tung University, Ph. D Programming Student
School of Business Administration, Southwestern University of Finance and Economics. 408, Ling-Tung Rd., Taichung, Taiwan, R.O.C.
Tel:+886-4-2389-2088 ext:3552
E-mail: gallen@mail.ltu.edu.tw

Abstract: Forecasting demand by taking into considerations the present international air cargo market and its possible changes in the future trend will assist in the construction for civil aviation policy and the planning of international airports. When forecasting air cargo volumes, due to the fact that uncertainty factors often cause deviation in estimations derived from traditional linear regression analysis, fuzzy regression analysis has been adopted to amalgamate with linear regression analysis, for reducing the residual resulted from uncertain factors. In this study, relative researches were presented to indicate the factors influencing export air cargo volume. Stepwise regression was implemented to find out key variable factors that had major impacts on Taiwan air cargo export and import volume. In addition, fuzzy regression analysis and volatility concept were applied to accurately forecast the demand for Taiwan air cargo volumes under present scenario.

Key Words: Air cargo, Freight Forecasting, Fuzzy Linear Regression

1. INTRODUCTION

In order to achieve the target of global logistic management, reliance on efficient and safe
deliveries via air transportation is relatively high. Respective to changes in the structure of international trade, and to further promote rapid growth in international air cargo volume, global civil aviation restrictions are gradually being loosen, which in the future might become barrier free, for example after 1997, all airlines can freely enter Europe (Hamoen, 1999). The government should understand its own trade and transportation needs when facing economic scenario changes and its consequences, in order to form the fundamental basis for planning of civil aviation policy and international airports and cargo terminals. In addition, the present and future possible trends of international air cargo market will be discussed in order to increase understanding to world air cargo transportation, and provide valuable reference to airlines, cargo terminals and civil aviation decision makers.

It is clear that air transportation is part of the service industry, hence a necessity to comply with the shippers’ needs. At present, the basic requirements from air cargo shippers are efficient delivery of goods, short preparation time and consistent service quality. When compared to other transportation models, the greatest advantages provided by air transportation are its efficiency and timely manner. To achieve the aforementioned target, advanced and efficient handling of airport ground cargo terminal is very important (Liang, et al., 2005). On the other hand, the planning and construction of new airports are dependent on references that are complete and detailed. Therefore study of air cargo volume forecast model in this research is vital and urgent.

In second and third sections, this article will present the fuzzy set of linear regression model as well as a precise description of assembled theories in order to give readers a firm grasps of the principles. In addition, the structure of fuzzy linear regression forecasting model (FRFM) will be presented in the fourth section. The forecast empirical discussion of Taiwan air cargo export and import volume and the verification of the FRFM will be stated in section five. The sixth section is the conclusion.

2. LITERATURE REVIEW OF FORECAST MODEL

There are only few papers regarding air cargo volume forecasts, at present the literatures that can contribute to this research are scarce. This is partly due to scholars and the public placed emphasis mostly on air passenger transport. As a result, most references are found on air passenger volume forecast or sea cargo volume forecast, but only limited references on air cargo volume forecast are available.

In a research report of A Study on Civil Aviation Development in Taiwan Area (Anonymous, 1996), the researchers used socioeconomic variables to construct traditional regression
forecast model to forecast passenger and cargo volume from 1997~2020. There are also other scholars who applied grey theory as basis to perform their studies. For example, Chen (1998) used grey theory, combined with Markov Chain, to build the forecast model for forecasting direct sea cargo volumes between Taiwan and China. Hsu and Wen (1997) applied grey forecast and grey assemble methods to forecast airline’s passenger quantity of different city pairs. Scholar Profiliidis (2000) used fuzzy linear regression model to forecast international air passenger volume. For forecasts regarding sea cargo volume, Lin (2000), Su (1998) used traditional linear regression, along with revised neural network, and fuzzy regression methods and applied them in the total volume forecast of Taiwan containerized cargos as well as total volume forecast of import and export cargoes.

To present a different approach other than the above mentioned literatures that used traditional linear regression method, symmetric triangular fuzzy regression method and grey theory, this study will adopt asymmetric triangular fuzzy set as the basis to construct the model for matching business reality in actual operational scenarios.

3. FUZZY SET THEORY

Intrinsically speaking, the thinking process, logic inference, and cognition to the surrounding environment are often vague and uncertain, consequently the forecast and predication based on traditional analytic methods which offered crisp value results often cannot accommodate for real life scenarios which are mostly indefinite and uncertain. Therefore Zadeh, in 1965, provided Fuzzy Set Theory, and Dubois and Prade (1978) proposed the fuzzy numbers and algorithm methods in 1978 to effectively eliminate vague and ambiguous data expression and transmission.

3.1 Fuzzy Set

Supposing $X$ is a collection of objects, either a single person or group of items denoted generically by $x$, then the fuzzy set $A$ is a set of ordered pairs: $A = \{ (x, f_A(x)) | x \in X \}$. When the definition region of function $f_A$ is $X$, and corresponding region is $[0,1]$, $f_A(x)$ is known as the grade of membership of $x$ in $A$. The closer the value of $f_A(x)$ is to 1, the higher grade of membership of $x$ is in $A$.

3.2 Triangular Fuzzy Numbers

Supposing there is a fuzzy number $A$, its grade of membership function is expressed as
\( f_A : \mathbb{R} \to [0,1] \), as shown by below (1), therefore fuzzy number \( A \) is defined as a triangular fuzzy number.

\[
\begin{align*}
  f_A(x) = & \begin{cases}
  x-c/a-c, & c \leq x \leq a \\
  x-b/a-b, & a \leq x \leq b \\
  0, & \text{o.w.}
  \end{cases}
\end{align*}
\]

(1)

In this formula \(-\infty < c \leq a \leq b < \infty\), the triangular fuzzy number \( A \) can be presented by \((c, a, b)\), so \( A = (c, a, b) \), as shown by Figure 1.

Figure 1. Membership Function of Triangular Fuzzy Number \( A = (c, a, b) \)

Triangular fuzzy number \( A \) has the largest grade of membership when the parameter value is \( a \), then \( f(a) = 1 \). It means that the value of the evaluation data, \( a \), has the highest probability to happen, so we define that the parameter of value \( a \) is the core of this triangular fuzzy number. The spread of this fuzzy number can be controlled by \( b \) and \( c \). The value of \( b-c \) is the spread of triangular fuzzy number \( A \). The more narrow the spread area, the less fuzzy the evaluation data is, hence more precise. On the other hand, the fuzziness becomes higher and therefore is vague and ambiguous. The reason for using triangular fuzzy numbers as the interpretation for analyzing data is because they can easily be mastered by decision makers for evaluation of economical analysis.

When stating “approximately 500”, it can be represented by \((495, 500, 505)\), in addition, it can be even more vaguely shown as \((485,500,515)\). On the other hand, a crisp number \( a \) can be expressed as \((a, a, a)\). When hypothesizing triangular fuzzy number \( A_1 = (c_1, a_1, b_1) \) and \( A_2 = (c_2, a_2, b_2) \), according to Zadeh’s Extension Principle, the extended algebraic operations of any two triangular fuzzy numbers \( A_1 = (c_1, a_1, b_1) \) and \( A_2 = (c_2, a_2, b_2) \) can be expressed as follows:

1. Addition
\( A_1 \oplus A_2 = (c_1+c_2, a_1+a_2, b_1+b_2) \)

2. Subtraction
\( A_1 \ominus A_2 = (c_1-b_2, a_1-a_2, b_1-c_2) \)

3. Multiplication
\( k \otimes A_1 = (kc_1, ka_1, kb_1) \), \( k \in \mathbb{R} \), \( k \geq 0 \)
4. FUZZY LINEAR REGRESSION MODEL

4.1 Fuzzy Linear Regression

In order to deal with vague data, Tanaka (1982) brought up the algorithm of fuzzy linear regression analysis. The concept of this method was that the residual between estimators and observations weren’t caused by measurement error, but rather the residual was caused by some uncertain parameters in the model. Therefore the fuzzy linear regression analysis emphasized that the parameters and variables in the model are both fuzzy numbers. The fundamental model of fuzzy linear regression analysis can be shown as the formula as below:

\[ Y = A_0X_0 + A_1X_1 + A_2X_2 + \Lambda + A_iX_i + \Lambda + A_pX_p \]

Where \( A_i, i=0,1,2,...p \) is set as triangular fuzzy numbers, and \( X_0=1, X_i>0, i=1,2,...p \) are all variables with crisp values, and assuming fuzzy parameter \( A_i=(c_i, a_i, b_i), i=0,1,2,...p \), then according to the calculation process for triangular fuzzy numbers stated in section 3.2, fuzzy number \( Y \) can be shown as follows:

\[ Y = \left( \sum_{i=0}^{p} c_i x_i, \sum_{i=0}^{p} a_i x_i, \sum_{i=0}^{p} b_i x_i \right) \]

The membership function of \( Y \) can be presented by \( f_Y(x) \), as follows:

\[
f_Y(x) = \begin{cases} 
  \frac{x - \sum_{i=0}^{p} c_i x_i}{\sum_{i=0}^{p} a_i x_i - \sum_{i=0}^{p} c_i x_i}, & \sum_{i=0}^{p} c_i x_i \leq x \leq \sum_{i=0}^{p} a_i x_i \\
  \frac{x - \sum_{i=0}^{p} b_i x_i}{\sum_{i=0}^{p} a_i x_i - \sum_{i=0}^{p} b_i x_i}, & \sum_{i=0}^{p} a_i x_i \leq x \leq \sum_{i=0}^{p} b_i x_i \\
  0, & \text{o.w.}
\end{cases}
\]

(2)

Assuming \( X_{ij}, i=1,2,..., p; j=1,2,..., n \) represents the \( i \)th independent observation in the \( j \)th sample, \( Y_j \) is an observation corresponding to \( j \)th sample, as a result, \( Y_j \) is a triangular fuzzy
number expressed as 

\[ Y_j = (d_j, e_j, f_j) \]

with a membership function \( f_{Y_j}(x) \) shown as follows:

\[
f_{Y_j}(x) = \begin{cases} 
\frac{x - d_j}{e_j - d_j}, & d_j \leq x \leq e_j \\
\frac{x - f_j}{e_j - f_j}, & e_j \leq x \leq f_j \\
0, & \text{o.w.}
\end{cases}
\]

Definition 1: The \( h \)-cut of fuzzy number \( A \) is represented by \( A^h \), where

\[ A^h = \{ x | f_{A}(x) \geq h, \ h \geq 0 \} \]

Definition 2: Assuming \( Y_j \) and \( \hat{Y}_j \) are the observations and estimators of the \( j \)th sample, the largest value of \( h_j \) will establish \( Y_j^{h_j} \subset \hat{Y}_j \), and therefore can be defined as the fitness evaluation value for \( j \)th sample.

The aforementioned fitness evaluation value \( h_j \) is an important indicator to examine the observations and estimators of \( j \)th sample. The more fit value of a sample, the better the level of fit between observation \( Y_j \) and estimator \( \hat{Y}_j \).

Assuming \( \hat{Y_j} = (m_j, n_j, o_j) \) is the estimator of \( j \)th sample’s observation \( Y_j \), then from equation (2), \( m_j = \sum_{i=0}^{e} c_i x_i, n_j = \sum_{i=0}^{a} a_i x_i, o_j = \sum_{i=0}^{b} b_i x_i \) can be obtained. If \( Y_j^{h_j} \subset \hat{Y}_j \), then \( h_j \) can be achieved by using (3) or (4).

For Scenario 1: \( e_j > n_j, o_j > f_j \) and \( d_j > m_j \)

As shown by Figure 2, by using equation (2), \( h_j \) can be derived from the following process:

\[ d = (e_j - n_j) + (1 - h_j)(f_j - e_j) \]

and \( 1 : (1 - h_j) = (o_j - n_j) : d \)

Therefore

\[ h_j = 1 - \frac{e_j - n_j}{(o_j - n_j) - (f_j - e_j)} \]  \hspace{1cm} (3)
Figure 2 The comprehending relation of observation $Y_j$ and estimator $\hat{Y}_j$ in Scenario 1.

For Scenario 2: $m_j < d_j, e_j < n_j$ and $o_j > f_j$

As shown by Figure 3, by using equation (2), $h_j$ can be derived from the following process:

$$d = (n_j - e_j) + (1 - h_j)(e_j - d_j)$$

and $1: (1 - h_j) = (n_j - m_j): d$

$$h_j = 1 - \frac{n_j - e_j}{(d_j - m_j) + (n_j - e_j)} \tag{4}$$

Figure 3 The comprehending relation of observation $Y_j$ and estimator $\hat{Y}_j$ in Scenario 2.

The value of $h$ is a threshold for estimating $c_i, a_i$ and $b_i$, and all fit evaluation value $h_j$ for observations and estimators should be greater than or equal to $h$, in which $h_j \geq h, j = 1, 2, \ldots n$. Therefore by taking equations (3) and (4) in Scenarios 1 and 2, two limitations can be obtained.
Subject to the above mentioned 2 limitations expressed in equation (5) and (6), in order to achieve the most accurate result, the fuzzy estimator $\hat{Y}_j$ observed from triangular membership function with the smallest spread is more precise. As a result, the target function of fuzzy parameter $A_i = (c_i, a_i, b_i)$ from summing up all of the triangular membership functions’ spread of the sample estimators subject to equations (5) and (6). Thus one can define the target function of minimum total amount of the spread with $n$ sample estimators is as follows:

$$\min J = \sum_{j=1}^{n}((b_0 - c_0) + (b_i - c_i)\|x_i\| + (b_2 - c_2)\|x_2\| + \ldots + (b_p - c_p)\|x_p\|)$$

4.2 Application of Scenario Index

In practical business activities, economic circulatory fluctuation is constantly present, hence upon its influence to future economic trend, the more the volatility of real life business scenarios can be mastered, the more credible the estimation results will be. $\alpha$-cut value can be used to represent the volatility of different business economic scenarios. When dealing with forecasts that have an explicit scenario and associating information can be grasped, larger $\alpha$-cut value can be taken. On the other hand, if facing ambiguous forecasts and crucial information are not made available, then a smaller $\alpha$-cut value can be chosen; hence the most ambiguous scenario will be represented by $\alpha = 0$, while $\alpha = 1$ represents the most definite scenario. Therefore this study will apply the concept of scenario index to allow for estimation result variations according to different scenario status, which will greatly enhance the practicality of this research.

$$\hat{Y}_\lambda^\alpha = \lambda \times U^\alpha_{\hat{Y}} + (1 - \lambda) \times L^\alpha_{\hat{Y}}$$

By adopting Triangular Fuzzy $A_i = (c_i, a_i, b_i), i = 0,1,2,\Lambda, p$, then alpha cut $A_i$, according to table $[L^\alpha_{A_i}, U^\alpha_{A_i}]$, result is shown by $[L^\alpha_{A_i}, U^\alpha_{A_i}] = [(a_i - c_i)\alpha + c_i, -(b_i - a_i)\alpha + b_i]$. Therefore Fuzzy Regression value is $\hat{Y} = \sum_{i=0}^{p} c_i x_i, \sum_{i=0}^{p} a_i x_i, \sum_{i=0}^{p} b_i x_i$, subject to alpha cut, shown by
Table $[L_i^a, U_i^a]$, its upper and lower boundaries are shown as

$$[L_i^a, U_i^a] = \left[ \sum_{j=0}^{p} x_j (a_j - c_j) \alpha + c_j, \sum_{j=0}^{p} x_j (b_j - a_j) \alpha + b_j \right].$$

After obtaining the upper and lower boundaries of fuzzy regression where scenario index has been taken into consideration, if the forecast is represented by a single observation, then index of optimism $\lambda$ derived from scholars, experts, or any related data can be merged into the analysis. If the economic data from scholars and exports is relatively optimistic, then the forecast singular value $\hat{Y}_\lambda^a$ will be indicated in the upper boundary, on the other hand, if their opinions are more pessimistic, then $\hat{Y}_\lambda^a$ can be found in the lower boundary.

$$\hat{Y}_\lambda^a = \lambda \times U_i^a + (1 - \lambda) \times L_i^a$$

In the above formula, $\lambda$ is called Index of optimism, it can be used to represent the decision maker’s level of optimism.

5. EMPIRICAL STUDY

5.1 Characteristics of Taiwan Air Cargo Exports Market

Based on statistical data, goods exported from Taiwan can be classified into 16 categories, of which the majorities are marine products, canned food and drinks, cigarettes, electronic devices, precision instruments and toys. Taiwan’s present export market product types not only coincide with Well’s (1998) statement of main air cargo products being fresh produce, electronics, computer soft and hardware, sporting equipments and toys, but also concur with the function of high percentage (nearly 50%) of goods demanding air transportation due to timeliness and preciousness features (http://www.iot.gov.tw).

5.2 Choosing Probable Variables

Before establishing a method to forecast the amount of cargo transported by air, one must first analyze and investigate the factors involved in order to understand which factors influence the estimation of air cargo and then select suitable methods to explain the variables and thus strengthen the ability to make forecasts.
Many factors can influence the amount of goods transported by air, including the economy, expansion of manufacturing system, and related characteristics of the corresponding trading areas. Therefore, the total exports volume via air is subject to the rate of economic growth, currency offerings, profit levels and currency exchange rates. This paper examined Taiwan air cargo exports volume by using principal variables such as Taiwan’s economy and manufacturing structure, economic growth rate, NT$:US$ exchange rate and the gross volume of national production.

(1) Economic Growth Rate: The higher the economic growth rate in a particular area, the more intense the economic activities will be, therefore will most definitely affect the volume of air cargoes.

(2) Foreign Exchange Rate: Transitions in international currency exchange rates will also affect the value of goods being exchanged, therefore this article emphasized on the importance of the exchange rate between NT$ and US$, hence this factor has been chosen as the initial variable for the test model.

(3) Gross Volume of national production (GDP): The level of a country’s gross national production represents the national manufacturing ability. It not only affects the nation’s consumer power but also has significant impact on its export ability. Therefore this factor has also been taken into consideration in the analysis.

5.3 Construction of Taiwan export Air Cargo Capacity Forecasting Model

5.3.1 Theory foundation

The fuzzy regression model of this research is based on the concept of Cobb-Douglas production function. This is shown as equation (7).

\[ Y = \beta_0 \prod_{i=1}^{p} x_i^{\beta_i} \]  

By natural logarithmic transformation, a linear function can be obtained. This research used the linear function to form the fuzzy linear regression model, see equation (8).

\[ \ln Y = \ln \beta_0 + \sum_{i=1}^{p} \beta_i \ln x_i \]  

By collecting data such as GDP and economic growth rate (see Table 1), and transforming them using natural logarithmic method, a forecasting fuzzy regression model for Taiwan air export cargo volume can easily is set.
Table 1 Yearly data of Taiwan Empirical Forecast Variables

<table>
<thead>
<tr>
<th>Year</th>
<th>Air Cargo Volume (10 k tones)</th>
<th>Economic Growth Rate (%)</th>
<th>Foreign Exchange Rate</th>
<th>GDP (bilIon)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>74.4398094</td>
<td>6.42</td>
<td>27.27</td>
<td>7.017900</td>
</tr>
<tr>
<td>1996</td>
<td>79.1802782</td>
<td>6.1</td>
<td>27.46</td>
<td>7.944595</td>
</tr>
<tr>
<td>1997</td>
<td>90.9899953</td>
<td>6.68</td>
<td>28.70</td>
<td>8.610139</td>
</tr>
<tr>
<td>1998</td>
<td>93.6402531</td>
<td>4.57</td>
<td>33.46</td>
<td>9.238472</td>
</tr>
<tr>
<td>1999</td>
<td>106.428945</td>
<td>5.42</td>
<td>32.27</td>
<td>9.640893</td>
</tr>
<tr>
<td>2000</td>
<td>121.485869</td>
<td>5.77</td>
<td>31.23</td>
<td>10.032004</td>
</tr>
<tr>
<td>2001</td>
<td>103.55524</td>
<td>-2.17</td>
<td>33.81</td>
<td>9.862183</td>
</tr>
<tr>
<td>2002</td>
<td>113.760287</td>
<td>4.25</td>
<td>34.58</td>
<td>10.194278</td>
</tr>
<tr>
<td>2003</td>
<td>118.603197</td>
<td>3.43</td>
<td>34.42</td>
<td>10.318610</td>
</tr>
<tr>
<td>2004</td>
<td>125.488856</td>
<td>6.07</td>
<td>33.43</td>
<td>10.770434</td>
</tr>
<tr>
<td>2005</td>
<td>120.317774</td>
<td>4.03</td>
<td>32.18</td>
<td>11.146783</td>
</tr>
</tbody>
</table>

5.3.2 Calculation Result

Firstly, according to data derived from natural logarithmic method transfer, three variables were chosen and stepwise regression analysis was applied. GDP was determined to be the major factor which had distinctive influence on Taiwan air export cargo volume, in which this model can be explicitly demonstrated by its significance, reaching 92.5%. Therefore, construction of the forecasting model will be based on an explanation of this variable factor. From results shown, the fuzzy linear regression model can be expressed as follows:

\[
\ln Y = A_0 + A_1 \ln(GDP)
\]

According to fuzzy regression parameter estimation, subject to fit evaluation value \( \alpha \) equals 0.5, the target function of minimum sum of the spread with \( n \) sample estimators can be obtained. Hence the limitation equation can be set up as follows:

\[
\begin{align*}
\min J &= \sum_j ((b_j - c_0) + (b_j - c_1) |x_{j1}| + (b_j - c_2) |x_{j2}| + \ldots \ldots + (b_j - c_p) |x_{jp}|) \\
&= 11b_0 -11c_0 - 24.7015b_1 - 24.7015c_1 \\
o_j + n_j &\geq 2e_j, \quad m_j + n_j \leq 2e_j, \quad j = 1, 2, \ldots, n
\end{align*}
\]

By using linear programming, the above linear regression can be resolved (\( \alpha = 0.5 \)), and fuzzy regression parameters of CKS Airport import and export air cargo volume obtained (as
shown in Table 2).

Table 2 Each regression parameters’ core and spread degree of FRFM

<table>
<thead>
<tr>
<th>$c_0$</th>
<th>$a_0$</th>
<th>$b_0$</th>
<th>$c_1$</th>
<th>$a_1$</th>
<th>$b_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.504311</td>
<td>1.639048</td>
<td>1.639048</td>
<td>1.334808</td>
<td>1.334808</td>
<td>1.406780</td>
</tr>
</tbody>
</table>

Table 3 Traditional regression estimators compared to fuzzy forecast value based on $\alpha=0.4$

<table>
<thead>
<tr>
<th>year</th>
<th>Air Cargo Volume (10 k tonnes)</th>
<th>GDP (billion)</th>
<th>ln(Air Cargo Volume)</th>
<th>ln(GDP)</th>
<th>$L_{\alpha}^\tilde{y}$</th>
<th>$U_{\alpha}^\tilde{y}$</th>
<th>Traditional Regression Estimators</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>74.4398094</td>
<td>7.017900</td>
<td>4.30999</td>
<td>1.94846</td>
<td>73.242</td>
<td>75.491</td>
<td>71.15704</td>
</tr>
<tr>
<td>1996</td>
<td>79.1802782</td>
<td>7.944595</td>
<td>4.37173</td>
<td>2.07249</td>
<td>75.534</td>
<td>89.561</td>
<td>83.02816</td>
</tr>
<tr>
<td>1997</td>
<td>90.9899953</td>
<td>8.610139</td>
<td>4.51075</td>
<td>2.15294</td>
<td>84.097</td>
<td>100.061</td>
<td>91.76748</td>
</tr>
<tr>
<td>1998</td>
<td>93.6402531</td>
<td>9.238472</td>
<td>4.53946</td>
<td>2.22338</td>
<td>92.387</td>
<td>110.260</td>
<td>100.17116</td>
</tr>
<tr>
<td>2000</td>
<td>121.485869</td>
<td>10.032004</td>
<td>4.79980</td>
<td>2.30578</td>
<td>103.129</td>
<td>123.519</td>
<td>110.98453</td>
</tr>
<tr>
<td>2001</td>
<td>103.55524</td>
<td>9.862183</td>
<td>4.64011</td>
<td>2.28871</td>
<td>100.805</td>
<td>120.647</td>
<td>108.65222</td>
</tr>
<tr>
<td>2002</td>
<td>113.760287</td>
<td>10.194278</td>
<td>4.73409</td>
<td>2.32183</td>
<td>105.362</td>
<td>126.280</td>
<td>113.22220</td>
</tr>
<tr>
<td>2003</td>
<td>118.603197</td>
<td>10.318610</td>
<td>4.77578</td>
<td>2.33395</td>
<td>107.080</td>
<td>128.408</td>
<td>114.94257</td>
</tr>
<tr>
<td>2004</td>
<td>125.488856</td>
<td>10.770434</td>
<td>4.83222</td>
<td>2.37680</td>
<td>113.384</td>
<td>136.219</td>
<td>121.23674</td>
</tr>
<tr>
<td>2005</td>
<td>120.313774</td>
<td>11.146783</td>
<td>4.79010</td>
<td>2.41115</td>
<td>118.704</td>
<td>142.821</td>
<td>126.52903</td>
</tr>
</tbody>
</table>

From Table 3, it is clear that in the fuzzy regression forecast model of Taiwan import and export air cargo volume when $\alpha=0.4$, the values obtained are triangular fuzzy numbers mainly $A_0=(1.5582, 1.6308, 1.6305)$, and the independent variable GDP’s parameter values are $A_1=(1.3348, 1.3348, 1.38)$. By using this result, the upper and lower bound of yearly fuzzy estimate values derived from different $\alpha$ cut $\left[L_{\alpha}^\tilde{y}, U_{\alpha}^\tilde{y}\right]$ can be acquired. Table 4 will present examples showing result from different calculations when $\alpha=0.4$ as well as listing all estimate values of traditional regression model. From this FRFM, the yearly fuzzy estimate values of import and export air cargo volume can be obtained. Furthermore, Index of Optimism $\lambda$ will be added to FRFM to get even more accurate forecast results.

By using different $\alpha$ values based on 0, 0.2, 0.4, 0.6, 0.8 and 1 on year 2004’s fuzzy regression estimate value $\tilde{Y}$, then added in different Index of Optimism $\lambda$ using 0, 0.2, 0.5, 0.8 and 1, the single estimate value $\tilde{Y}_\lambda^\alpha$ can be acquired from the aforementioned various economic scenario and Index of Optimism as shown by Table 4.

Table 4 Single value of $\tilde{Y}_\lambda^\alpha$ under various economic scenarios and Index of Optimism (unit: 10 k tonnes)
Table 4 clearly stated the 30 estimate values of 2004 Taiwan air cargo volume analyzed under various economic scenarios $\alpha$ and Index of Optimism $\lambda$. At this point in time the decision maker can easily make the right decisions based on whatever information one has on hand. For example in year 2004’s data verification, when the information on hand is incomplete, based on $\alpha$ cut at 0.6, subject to a neutral social economic scenario being Index of Optimism $\lambda=0.5$, the total import and export air cargo volume is shown as 124.0594 ten thousand tonnes, this figure is smaller than the actual value of 125.489 ten thousand tonnes. The absolute deviation is 1.139%. From this it can be acknowledged that the economic scenario at that time was under major changes, furthermore, due to influences of global recession, the decision maker’s attitude towards risk should be more conservative and pessimistic. This forecast result is far more accurate than the estimate value of 121.2367 ten thousand tonnes derived from traditional linear regression model, with an absolute deviation of 3.39%.

On the other hand, when forecasting 2006’s air cargo volume, if the decision maker judged the economic scenario of that year to be an economic recovery year, accordingly its decision will be based on an optimistic attitude and therefore Index of Optimism $\lambda=0.8$ was used, in the mean time, due to information gathering was more complete, hence $\alpha$-cut of 0.8 can be used. After calculating by above information of $\lambda$ and $\alpha$-cut, the result of $\alpha^\lambda$ $Y_\lambda$ in 2006 is 137.76 has very little variance when compared to the actual value of 144.620 ten thousand tonnes, with absolute deviation of 4.98%. Therefore, the FRFM built by this study when applied to the practicality of forecasting, the accuracy level is extremely high.

6. CONCLUSION

It is important to understand in advance national trade, requirements of air transportation, and influences on business development resulting from various operation scenarios. In addition, upon defining changes in international air cargo market, along with accurately predicting the air cargo volume, useful references can be obtained for the discreet planning of national civil aviation policy and for business operations in international airports. Through fuzzy regression forecast model formed by applying the uncertainty factors from real life scenarios, such as Index of Optimism, a more flexible and persuasive future volume forecast can be
achieved.

This research has presented a forecast model that can accurately forecast future Taiwan air cargo exports volume using GDP as the main influential variable. The fuzzy regression forecast model used was unlike the traditional symmetric triangular fuzzy method, but rather it had adopted the asymmetric triangular fuzzy method to enhance the practicality and reliability of this FRFM.

Along with the increase in air cargo volume, relative industries’ operational and marketing strategies from different countries in air cargo should be considered as early as possible, in order to construct a plan prioritizing the different requirements faced in different phases.

REFERENCES

Liang, G. S., Han, T. C. and Chou, T. Y. (2005) Using a fuzzy quality function deployment model to identify airport cargo terminal improvement points, Transportation Research Record, No. 1935, pp. 130-140.
Su, C. C. (1998) Forecasting the Freight of Taichung port import and export cargo, Department of Shipping and Transportation Management National Taiwan Ocean University, master thesis.

