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Forecasting tourist arrivals by using the adaptive network-based fuzzy inference system

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ABSTRACT

Since accurate forecasting of tourist arrivals is very important for planning for potential tourism demand and improving the tourism infrastructure, various tourist arrivals forecasting methods have been developed. The purpose of this study is to apply the adaptive network-based fuzzy inference system (ANFIS) model to forecast the tourist arrivals to Taiwan and demonstrate the forecasting performance of this model. Based on the mean absolute percentage errors and statistical results, we can see that the ANFIS model has better forecasting performance than the fuzzy time series model, grey forecasting model and Markov residual modified model. Thus, the ANFIS model is a promising alternative for forecasting the tourist arrivals. We also use the ANFIS model to forecast the monthly tourist arrivals to Taiwan from Japan, Hong Kong and Macao, and the United States.

1. Introduction

The tourism industry has grown rapidly over the past few decades. Due to the perishable nature of the tourism industry, the need for accurate forecasts is crucial. Both the public non-profit government sectors and the private profit companies are interested in finding an accurate forecasting technique to make operational, tactical and strategic decisions. Companies can, using the results from this forecasting technique, plan for potential tourism demand successfully and invest in tourism related facilities and equipments sufficiently, and government sectors can play a significant role in maintaining and improving tourism infrastructure. Therefore, various forecasting methods have been developed. They include exponential smoothing (Cho, 2003), ARIMA (Cho, 2003; Chu, 1998; Goh & Law, 2002; Lim & McAleer, 2002), vector autoregressive (Song & Witt, 2006; Wong, Song, & Chon, 2006), neural networks (Chen & Wang, 2007; Cho, 2003; Law, 2000; Law & Au, 1999), fuzzy time series (Wang, 2004; Wang & Hsu, 2008), grey model (Hsu & Wen, 1998; Wang, 2004), econometric (Hiemstra & Wong, 2002; Smeral, Witt, & Witt, 1992; Song & Witt, 2000; Witt & Martin, 1987), regression-based model (Chan, 1993; Crouch, Schultz, & Valerio, 1992; Kulendran & Witt, 2001) and genetic algorithm (Chan, 2007; Hernández-López & Cáceres-Hernández, 2007; Hernández-López, 2004; Hurley, Moutinho, & Witt, 1998). But we can not find any paper adopting an adaptive network-based fuzzy inference system, referred to as ANFIS (Jang, 1993), to forecast tourist arrivals. So, the purpose of this paper is to fill this gap, and we also try to compare the results with those of other models and use the ANFIS model to forecast the monthly tourist arrivals to Taiwan from the top three markets.

In this paper, the data used were from the Tourism Bureau of Republic of China (ROC), and, for comparison, the annual tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany from 1989 to 2003 were considered. But, according to the numbers of tourist arrivals to Taiwan, we apply the ANFIS to forecast the monthly tourist arrivals to Taiwan from the top three markets: Japan, Hong Kong and Macao, and the United States.

The rest of this paper is organized as follows: Section 2 introduces the architecture and the hybrid learning algorithm of an ANFIS with a simple illustration. Section 3 compares the forecasting accuracy for the different models. Section 4 presents the application of the ANFIS to forecast the monthly tourist arrivals to Taiwan from Japan, Hong Kong and Macao, and the United States. The last section contains some concluding remarks.

2. Adaptive network-based fuzzy inference system

An ANFIS (Jang, 1993) can help us find the mapping relation between the input and output data through hybrid learning to determine the optimal distribution of membership functions. Five layers are used to construct this inference system. Each layer contains several nodes described by the node function. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable...
in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system. The output data from the nodes in the previous layers will be the input in the present layer.

To illustrate the procedures of an ANFIS, for simplicity, we consider only two inputs \( x, y \) and one output \( f_{\text{out}} \) in this system. The framework of ANFIS is shown in Fig. 1, and the node function in each layer is described below.

Layer 1: Every node in this layer is an adaptive node with node function as:
\[
O_{1,i} = \mu_A(x), \quad \text{for} \quad i = 1, 2
\]
\[
O_{1,i} = \mu_B(y), \quad \text{for} \quad i = 3, 4
\]
where \( x \) (or \( y \)) is the input of the node, \( A \) (or \( B \)) is the linguistic label, \( \mu_A(x) \) (or \( \mu_B(y) \)) is the membership function, usually adopting bell shape with maximum and minimum equal to 1 and 0, respectively, as follows:
\[
\mu(x) = \frac{1}{1 + \left(\frac{x - c}{a}\right)^2}
\]
or
\[
\mu(x) = \exp\left\{-\left(\frac{x - c}{a}\right)^2\right\}
\]
where \( \{a, b, c\} \) is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly. The parameters in this layer are named premise parameters.

Layer 2: Every node in this layer is a fixed node, marked by a circle and labeled \( \Pi \), with the node function to be multiplied by input signals to serve as output signal
\[
O_{2,i} = \mu_A(x) \cdot \mu_B(y) = \omega_i \quad \text{for} \quad i = 1, 2
\]
The output signal \( \omega_i \) represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node, marked by a circle and labeled \( N \), with the node function to normalize the firing strength by calculating the ratio of the ith node firing strength to the sum of all rules’ firing strength.
\[
O_{3,i} = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} = \bar{\omega}_i \quad \text{for} \quad i = 1, 2
\]

Layer 4: Every node in this layer is an adaptive node, marked by a square, with node function
\[
O_{4,i} = \bar{\omega}_i \cdot f_i \quad \text{for} \quad i = 1, 2
\]
where \( f_1 \) and \( f_2 \) are the fuzzy if-then rules as follows:

Rule 1: if \( x \) is \( A_1 \) and \( y \) is \( B_1 \) then \( f_1 = p_1 x + q_1 y + r_1 \)

Rule 2: if \( x \) is \( A_2 \) and \( y \) is \( B_2 \) then \( f_2 = p_2 x + q_2 y + r_2 \)

and where \( \{p_1, q_1, r_1\} \) is the parameters set, referred to as the consequent parameters.

Layer 5: Every node in this layer is a fixed node, marked by a circle and labeled \( \Sigma \), with node function to compute the overall output by
\[
O_5 = \sum_i \bar{\omega}_i \cdot f_i = f_{\text{out}}
\]

As mentioned above, an ANFIS is a multilayer feedforward network in which each node performs a node function on incoming signals as well as a set of parameters belonging to this node. Suppose that the given training data set has \( n \) entries. We define the overall error measure by
\[
E = \sum_{i=1}^{n} \left( T_i - f_{\text{out}} \right)^2
\]
where \( E_i \) is the error measure for the \( i \)th entry of the given training data set, \( T_i \) is the desired output of the \( i \)th entry and \( f_{\text{out}} \) is the output of the ANFIS using the \( i \)th entry.

From the architecture of the ANFIS, we know that if the premise parameters \( \{a, b, c\} \) are fixed, the output \( f_{\text{out}} \) of the whole system will be a linear combination of the consequent parameters \( \{p_1, q_1, r_1\} \) as follows:
\[
f_{\text{out}} = \sum_i \bar{\omega}_i \cdot f_i = \bar{\omega}_1 \cdot f_1 + \bar{\omega}_2 \cdot f_2 = \bar{\omega}_1 (p_1 x + q_1 y + r_1)
\]
\[
+ \bar{\omega}_2 (p_2 x + q_2 y + r_2) = (\bar{\omega}_1 p_1 + (\bar{\omega}_1 q_1 + \bar{\omega}_1 r_1)
\]
\[
+ (\bar{\omega}_2 p_2 + (\bar{\omega}_2 q_2 + \bar{\omega}_2 r_2)
\]

Let matrices
\[
\begin{bmatrix}
f_{\text{out}}
f_{\text{out}1}
f_{\text{out}2}
f_{\text{out}3}
f_{\text{out}4}
f_{\text{out}5}
\end{bmatrix}
= \begin{bmatrix}
p_1 
q_1 
\vdots 
r_1 
p_2 
q_2 
\vdots 
r_2 
\vdots 
\vdots 
\vdots 
p_9 
q_9 
\vdots 
r_9 
\end{bmatrix}, \quad \text{and}
\begin{bmatrix}
\bar{\omega}_1 x_1 & \bar{\omega}_1 y_1 & \bar{\omega}_1 & \bar{\omega}_1 x_1 & \bar{\omega}_1 y_1 & \bar{\omega}_1 & 
\bar{\omega}_2 x_2 & \bar{\omega}_2 y_2 & \bar{\omega}_2 & \bar{\omega}_2 x_2 & \bar{\omega}_2 y_2 & \bar{\omega}_2 & 
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & 
\bar{\omega}_9 x_9 & \bar{\omega}_9 y_9 & \bar{\omega}_9 & \bar{\omega}_9 x_9 & \bar{\omega}_9 y_9 & \bar{\omega}_9 & 
\end{bmatrix}
\]

Then, Eq. (10) can be expressed in matrix form as
\[
f = B \theta
\]
where $\theta$ is an unknown matrix, whose elements come from the consequent parameters set. The least squares estimator (LSE) $\theta^*$ is given by

$$\theta^* = (B^TB)^{-1}B^T f$$

The hybrid learning algorithm of the ANFIS combines the gradient method with the least squares method to update the parameters in an adaptive network. Each epoch of this hybrid learning procedure is composed of a forward pass and a backward pass. In the forward pass, after every input vector is given, we calculate the corresponding node output until the matrices $B$ and $f$ in Eq. (11) are obtained. The parameters in the consequent parameters set are identified by using Eq. (13); then, we can compute the error measure by Eq. (9). In the backward pass, we have to calculate the error rate $\partial E / \partial O$ for the $i$th entry of the training data set and for each node output $O$. If $z$ is a parameter of the premise parameters set, by the chain rule, the derivative of the overall error measure $E$ with respect to $z$ is

$$\frac{\partial E}{\partial z} = \sum_{i=1}^{n} \frac{\partial E_i}{\partial O} = \sum_{i=1}^{n} \sum_{O_i \in V} \frac{\partial E_i}{\partial O} \frac{\partial O}{\partial z}$$

where $V$ is the set of nodes whose outputs depend on $z$, and $O$ is a node output belonging to $V$. Then, the updated formula for the premise parameter $z$ by the gradient method is given by

$$\Delta z = -\eta \frac{\partial E}{\partial z}$$

in which $\eta$ is a learning rate.

The computation of the data for the ANFIS was conducted using the software Matlab. The ANFIS training algorithms, including the gradient method and the least squares method, were embedded in the software of Matlab’s fuzzy inference toolbox. The main computation procedure includes four steps. The first step is the data input. The input of the event data includes the input data and output data in the form of data array. The second step is generating fuzzy inference system. The third step is using ANFIS training function in the toolbox for the training of the input data. The training of the data will be performed automatically in the system and an array of training error will be obtained. After training, an ANFIS model with forecasting function will be obtained for output forecasting at the last step.

3. Comparisons of forecasting accuracy for various models

In this section, for comparison with the results proposed by Wang (2004), we employed the annual tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany, shown in Table 1, from 1989 to 2003 as our research data. The data are divided into two data sets: the training data set (from 1989 to 2000) and the testing data set (from 2001 to 2003).

For the purposes of comparisons of the forecasting performances among various models, the absolute percentage error (APE) and the mean absolute percentage error (MAPE), given by Eqs. (16) and (17) respectively, are used as the indexes of forecasting accuracy. MAPE is a relative measurement and is easy to interpret. MAPE is also independent of scale, reliable and valid (Law & Au, 1999). The smaller the values of MAPE, the closer were the forecasted values to the actual values.

Table 1
The tourist arrivals to Taiwan from the three markets (from 1989 to 2003).

| Year | Hong Kong | The United States | Germany |
|------|-----------|-------------------|---------|
| 1989 | 211804    | 220594            | 25002   |
| 1990 | 193544    | 224915            | 24520   |
| 1991 | 181765    | 240375            | 25798   |
| 1992 | 193523    | 259145            | 28969   |
| 1993 | 213953    | 269110            | 28644   |
| 1994 | 241775    | 286713            | 31334   |
| 1995 | 246747    | 290138            | 32944   |
| 1996 | 262585    | 289900            | 33914   |
| 1997 | 259664    | 303634            | 34660   |
| 1998 | 279905    | 308407            | 35343   |
| 1999 | 319814    | 317801            | 34190   |
| 2000 | 361308    | 359533            | 34829   |
| 2001 | 392552    | 348808            | 33716   |
| 2002 | 456554    | 377470            | 33979   |
| 2003 | 323178    | 272858            | 28577   |

Fig. 2. Fuzzy rule architecture of the ANFIS. System ANFIS: two inputs, one output, and nine rules.

Fig. 3. Initial bell shaped membership functions of the three markets.
Wang (2004) proposed fuzzy time series, grey forecasting model GM(1,1) and Markov residual modified model to forecast the tourist arrivals to Taiwan from Hong Kong, the United States and Germany and found that the fuzzy time series is suitable for the tourism demand forecasting of Hong Kong arrivals, the GM(1,1) model is appropriate for the tourism demand forecasting of Hong Kong and the United States arrivals, and Markov residual modified model is the best for Germany tourism demand forecasting. This study used the ANFIS models to forecast the tourist arrivals to Taiwan from the three markets and compared the results with those of Wang (2004) with the help of software of Matlab’s fuzzy inference toolbox.

The input data are the annual tourist arrivals to Taiwan from the three markets: Hong Kong, the United States, and Germany from 1989 to 2000, shown in Table 1. Bell shaped functions were chosen for the membership function expressed in Eq. (3). Fig. 2 shows the fuzzy rule architecture of the ANFIS with two inputs, one output and a total of nine fuzzy rules. The initial value of step size for the training by the ANFIS was set to 0.011.

According to the settings above, the training process was performed using Matlab 7.0. The root mean square errors became steady after running 348, 210, and 840 epochs of training on data from Hong Kong, the United States, and Germany, respectively. The final convergence values were 2594.5373, 4234.712, and 334.8358 for Hong Kong, the United States, and Germany respectively. Figs. 3 and 4 showed the initial and final membership functions of the input data of the three markets respectively. After the training process, the trained ANFIS system could be used for forecasting. The forecasting results and corresponding MAPE values of the various forecasting models for the different markets are listed in Table 2.

For comparison, we only used the forecasting data from 1989 to 2000, of the various forecasting models. Table 2 shows that, for each market, in tourist arrivals forecasting, the ANFIS model has smaller MAPE values than the fuzzy time series, grey forecasting model GM(1,1) and Markov residual modified model; in other words, the forecasting performance of the ANFIS model is better than that of the other models.

Because each forecasting value of the various forecasting models corresponds to its actual value, these two values are matched. The Kolmogorov–Smirnov (K–S) test is used to test the hypothesis that the difference D of the matched data for various forecasting models is normally distributed. If we do not reject the hypothesis, we could establish a 95% confidence interval estimate of the mean of the difference of the matched data. Table 3 shows the statistical results of the p-values of the K–S test (p), the mean of the difference of matched data (D), and its upper bound (U), lower bound

Table 2
Forecasting results of the tourist arrivals to Taiwan from Hong Kong, the United States and Germany by various forecasting models.

| Year | Hong Kong | | | The United States | | | Germany | |
|------|-----------|---|---|-----------------|---|---|-----------------|---|
|      | ANFIS     | GM (1,1) | Markov | Fuzzy (w = 5) | ANFIS | GM (1,1) | Markov | Fuzzy (w = 3) | ANFIS | GM (1,1) | Markov | Fuzzy (w = 6) |
| 1989 | 211804    | 211804 | – | – | 220594 | 220594 | – | – | 25002 | 25002 | – |
| 1990 | 182293    | 193948 | – | – | 230349 | 223733 | – | – | 23921 | 24580 | – |
| 1991 | 193875    | 182850 | 196183 | 259901 | 242725 | 230349 | 223733 | – | 25802 | 26793 | 25433 |
| 1992 | 213598    | 223546 | 210340 | 268507 | 257754 | 265577 | 25921 | 26793 | 25433 | 25802 | 26793 |
| 1993 | 241738    | 239276 | 253044 | 289648 | 267595 | 275868 | 283557 | 31333 | 29589 | 31007 |
| 1994 | 247251    | 256113 | 241759 | 286570 | 277812 | 286506 | 301160 | 32942 | 30584 | 32022 |
| 1995 | 261944    | 274134 | 259170 | 258367 | 293808 | 288420 | 297970 | 298285 | 33926 | 31613 | 33071 |
| 1996 | 259824    | 293424 | 277822 | 274025 | 294904 | 299432 | 300213 | 317967 | 34705 | 32677 | 34155 |
| 1997 | 280031    | 314071 | 297805 | 264484 | 311326 | 310864 | 300521 | 318081 | 34506 | 33776 | 35275 |
| 1998 | 319755    | 336170 | 319213 | 305125 | 330341 | 322733 | 311796 | 310254 | 34155 | 34913 | 33393 |
| 1999 | 361314    | 325925 | 377504 | 351834 | 349375 | 335056 | 346222 | 332248 | 34899 | 36087 | 34546 |
| 2000 | 361314    | 325925 | 377504 | 351834 | 349375 | 335056 | 346222 | 332248 | 34899 | 36087 | 34546 |
| MAPE (%)| 0.0969 | 6.9094 | 3.9862 | 1.4957 | 3.0894 | 2.2725 | 3.5439 | 0.2992 | 4.3720 | 1.7713 | 2.6881 |
### Table 3
Statistical results of the difference of the matched data for various forecasting models and for different markets.

| Market          | Statistics | Actual to GM (1, 1) | Actual to Markov | Actual to Fuzzy | Actual to ANFIS |
|-----------------|------------|---------------------|------------------|-----------------|-----------------|
| Hong Kong       | p          | 0.866               | 0.420            | 0.921           | 0.673           |
|                 | \(\hat{p}\) | –10686.67           | –4597.92         | 5852.20         | 0.10            |
|                 | U          | –1980.04            | 968.81           | 21076.16        | 234.27          |
|                 | L          | –19393.30           | –10164.64        | –9371.76        | –234.07         |
|                 | W          | 17413.26            | 11133.45         | 30447.92        | 468.34          |
| The United States |           |                     |                  |                 |                 |
|                 | p          | 0.821               | 0.969            | 0.887           | 0.930           |
|                 | \(\hat{p}\) | 6019.75             | 2499.83          | 2970.57         | 59.65           |
|                 | U          | 12108.19            | 6678.49          | 15920.05        | 4726.54         |
|                 | L          | –68.69              | –1678.83         | –9978.91        | –4607.24        |
|                 | W          | 12176.88            | 8357.32          | 25898.96        | 9333.78         |
| Germany         | p          | 0.794               | 0.953            | 0.896           | 0.497           |
|                 | \(\hat{p}\) | 556.00              | 197.17           | –442.50         | 1.50            |
|                 | U          | 1491.99             | 594.05           | 1608.36         | 20.3792         |
|                 | L          | –379.99             | –199.72          | –2493.36        | –17.3792        |
|                 | W          | 1871.98             | 793.77           | 4101.72         | 37.7584         |

### Table 4
Forecasting results of the tourist arrivals to Taiwan from the three markets by the ANFIS model from 2001 to 2003.

| Model           | Year | 2001                      | 2002                      | 2003                      |
|-----------------|------|---------------------------|---------------------------|---------------------------|
|                 |      | GM (1, 1) (APE%)          | Markov (APE%)            | Fuzzy (APE%)             | ANFIS (APE%)          |
|                 |      |                           |                           |                           | ANFIS (APE%)          |
|                 |      |                           |                           |                           | ANFIS (APE%)          |
| Hong Kong       |      | 385144 (1.887)            | 366713 (6.582)            | 393232 (0.1732)           | 456295 (0.0567)       |
|                 |      |                           |                           |                           | 434692 (34.305)       |
| The United States |    | 347848 (0.275)            | 360079 (3.231)            | 349153 (0.0989)           | 377789 (0.0845)       |
|                 |      |                           |                           |                           | 369814 (35.534)       |
| Germany         |      | 37301 (10.634)            | 35739 (6.000)             | 34361 (1.9130)            | 34206 (0.6681)        |
|                 |      |                           |                           |                           | 34201 (19.680)        |

### Table 5
Forecasting results of the tourist arrivals to Taiwan from Japan, Hong Kong and Macao, and the United States by ANFIS models.

| Year and month | Japan | Hong Kong and Macao | The United States |
|---------------|-------|---------------------|-------------------|
|               | Actual | ANFIS               | Actual            | ANFIS               | Actual            | ANFIS               |
| 2006          |        |                     |                   |                   |                   |                   |
| January       | 85523  | –                   | –                 | 32414             | –                 | 31248             |
| February      | 99506  | –                   | 34124             | –                 | 32584             |
| March         | 109499 | 107644              | 34443             | 34554             | 32702             |
| April         | 84426  | 85519               | 42018             | 42090             | 32702             |
| May           | 90886  | 91212               | 35820             | 36415             | 32702             |
| June          | 91676  | 91785               | 39995             | 41120             | 40492             |
| July          | 81029  | 80188               | 38126             | 43538             | 36019             |
| August        | 98725  | 96527               | 44668             | 44070             | 29550             |
| September     | 102438 | 103709              | 32095             | 30681             | 26231             |
| October       | 103465 | 99863               | 28029             | 27791             | 34341             |
| November      | 114547 | 115002              | 28383             | 28582             | 34766             |
| December      | 99810  | 99979               | 41769             | 41726             | 37476             |
|               |        |                     |                   |                   |                   | 38221             |
| 2007          |        |                     |                   |                   |                   |                   |
| January       | 101563 | 102306              | 23879             | 23658             | 27712             |
| February      | 84736  | 97985               | 35289             | 35291             | 28892             |
| March         | 120599 | 120650              | 36283             | 36434             | 36044             |
| April         | 89021  | 89581               | 49732             | 48947             | 32199             |
| May           | 90784  | 90304               | 39057             | 38911             | 31551             |
| June          | 92127  | 92228               | 49526             | 49868             | 38982             |
| July          | 81116  | 83637               | 42788             | 43588             | 36351             |
| August        | 97975  | 101001              | 49586             | 49888             | 29970             |
| September     | 101584 | 102646              | 37729             | 37914             | 27100             |
| October       | 99419  | 94768               | 36549             | 37111             | 35495             |
| November      | 106875 | 108529              | 38047             | 41370             | 33668             |
| December      | 100761 | 101104              | 52972             | 46894             | 40001             |
|               |        |                     |                   |                   |                   | 39561             |
| 2008          |        |                     |                   |                   |                   |                   |
| January       | 98392  | 96756               | 30088             | 30143             | 30092             |
| February      | 92394  | 93371               | 50024             | 50106             | 27584             |
| March         | 106520 | 106867              | 56303             | 56426             | 38350             |
| April         | 82136  | 82537               | 43224             | 43245             | 31478             |
|               |        |                     |                   |                   |                   | 31531             |
| MAPE (%)      | 1.82236 |                   | 2.16596           |                   | 1.10851           |
Table 3 shows that all p-values of the K–S test are larger than 0.05, so we can not reject the hypothesis that the differences of matched data for the various forecasting models are normally distributed. From the results of the mean of difference $D$ and the 95% confidence interval estimate of the mean difference $D$ of the ANFIS model are the smallest among all the forecasting models except Markov residual modified model for the United States market; so, the ANFIS model seems to be more accurate than all the other models.

As mentioned above, based on the values of MAPE and confidence interval width from 1989 to 2000, the ANFIS model seems to be the most accurate one. It means that the ANFIS model is suitable for the tourist arrivals forecasting. Therefore, we use the ANFIS model to forecast tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany from 2001 to 2003, and compute the APE values of the three markets to present the forecasting accuracy of the ANFIS model.

Table 4 shows that all the APE values of Hong Kong, the United States and Germany by the ANFIS model are below 2% in 2001, less than those by the GM (1,1), Markov and fuzzy models, forecasted by Wang (2004). The reason why the APE values of the ANFIS model do not become so small in 2003, is probably due to the outlier data that happened during the Severe Acute Respiratory Syndrome (SARS).

4. Forecasting of the monthly tourist arrivals from the top three markets

According to the comparative results shown in the previous section, it could be concluded that the ANFIS model is superior to the others. Thus, the ANFIS model is a promising alternative for forecasting the tourist arrivals. In this section, we apply the ANFIS model to forecast the monthly tourist arrivals to Taiwan from the top three markets: Japan, Hong Kong and Macao, and the United States according to the volume of tourist arrivals from January 2006 to April 2008, shown in Table 5.

Bell shaped functions were chosen for the membership function defined in Eq. (3). The fuzzy rule architecture is the same as Fig. 2, and the initial value of step size for the training was set to 0.011. The root mean square errors became steady after running 9,247,690, 1,723,549, and 3,161,265 epochs of training on data from Japan, Hong Kong and Macao, and the United States respectively. The final convergence values were 3095.9057, 1792.0489, and 535.1169 for Japan, Hong Kong and Macao, and the United States respectively. Figs. 5 and 6 showed the initial and final membership functions of the input data respectively. After the training process, the trained ANFIS system could be used for forecasting.

Fig. 5. Initial bell shaped membership functions of the top three markets.

Fig. 6. Final membership functions of the top three markets.
The forecasting results and corresponding MAPE values of the various forecasting models for the top three markets are listed in Table 5. From Table 5 and Fig. 7, we can find that seasonal fluctuations occurred in the six time series, and the actual values and the ANFIS forecasting values for tourist arrivals to Taiwan from the top three markets are very close.

5. Conclusion

Accurate forecasting of tourist arrivals is helpful for planning for potential tourism demand to invest in tourism related facilities and equipments and improve tourism infrastructure. This study adopted the ANFIS model to forecast the tourist arrivals to Taiwan, and compared the MAPE and APE values and statistical results of the ANFIS with those of other models. The empirical results, obtained in Section 3, by the ANFIS model yield more accurate tourist arrivals forecasting than that of the other models. Therefore, we conclude that the ANFIS model is a valid and promising alternative for forecasting tourist arrivals. From the results of Section 4, we can see that, owing to seasonal variation, the monthly tourist arrivals forecasting has larger MAPE values than the annual data and the root mean square errors become steady until a great amount of epochs.

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