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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 (Chen & Wang, 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

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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_{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:

$$O_{1,i} = \mu_{A_i}(x), \quad \text{for} \quad i = 1, 2 \tag{1}$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for} \quad i = 3, 4 \tag{2}$$

where x(or y) is the input of the node, A_i(or B_j) is the linguistic label, $\mu(x)$(or $\mu(y)$) is the membership function, usually adopting bell shape with maximum and minimum equal to 1 and 0, respectively, as follows:

$$\mu(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2b_i}} \tag{3}$$

or

$$\mu(x) = \exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \tag{4}$$

where $\{a_i, b_i, c_i\}$ 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 $\prod$, with the node function to be multiplied by input signals to serve as output signal

$$O_{2,i} = \mu_{A_i}(x) \cdot \mu_{B_i}(y) = \omega_i \quad \text{for } i = 1, 2 \tag{5}$$

The output signal ω_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.

$$O_{3,i} = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} = \bar{\omega}_i \quad \text{for } i = 1, 2 \tag{6}$$

Layer 4: Every node in this layer is an adaptive node, marked by a square, with node function

$$O_{4,i} = \bar{\omega}_i \cdot f_i \quad \text{for } i = 1, 2 \tag{7}$$

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 $\{p_i, q_i, r_i\}$ 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 Σ, with node function to compute the overall output by

$$O_5 = \sum_i \bar{\omega}_i \cdot f_i = f_{out} \tag{8}$$

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

$$E = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} (T_i - f_{outi})^2 \tag{9}$$

where E_i is the error measure for the ith entry of the given training data set, T_i is the desired output of the ith entry and f_{outi} is the output of the ANFIS using the ith entry.

From the architecture of the ANFIS, we know that if the premise parameters $\{a_i, b_i, c_i\}$ are fixed, the output f_{outi} of the whole system will be a linear combination of the consequent parameters $\{p_i, q_i, r_i\}$ as follows:

$$\begin{aligned} f_{out} &= \sum \bar{\omega}_i \cdot f_i = \bar{\omega}_1 \cdot f_1 + \bar{\omega}_2 \cdot f_2 = \bar{\omega}_1(p_1 x + q_1 y + r_1) \\ &\quad + \bar{\omega}_2(p_2 x + q_2 y + r_2) = (\bar{\omega}_1 x)p_1 + (\bar{\omega}_1 y)q_1 + \bar{\omega}_1 r_1 \\ &\quad + (\bar{\omega}_2 x)p_2 + (\bar{\omega}_2 y)q_2 + \bar{\omega}_2 r_2 \end{aligned} \tag{10}$$

Let matrices

$$\boldsymbol{f} = \begin{bmatrix} f_{out1} \\ f_{out2} \\ \cdot \\ \cdot \\ \cdot \\ f_{outn} \end{bmatrix}, \quad \boldsymbol{\theta} = \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix}, \text{ and}$$

$$\mathbf{B} = \begin{bmatrix} \bar{\omega}_1 x_1 & \bar{\omega}_1 y_1 & \bar{\omega}_1 & \bar{\omega}_2 x_1 & \bar{\omega}_2 y_1 & \bar{\omega}_2 \\ \bar{\omega}_1 x_2 & \bar{\omega}_1 y_2 & \bar{\omega}_1 & \bar{\omega}_2 x_2 & \bar{\omega}_2 y_2 & \bar{\omega}_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \bar{\omega}_1 x_n & \bar{\omega}_1 y_n & \bar{\omega}_1 & \bar{\omega}_2 x_n & \bar{\omega}_2 y_n & \bar{\omega}_2 \end{bmatrix} \tag{11}$$

Then, Eq. (10) can be expressed in matrix form as

$$\boldsymbol{f} = \mathbf{B}\boldsymbol{\theta} \tag{12}$$

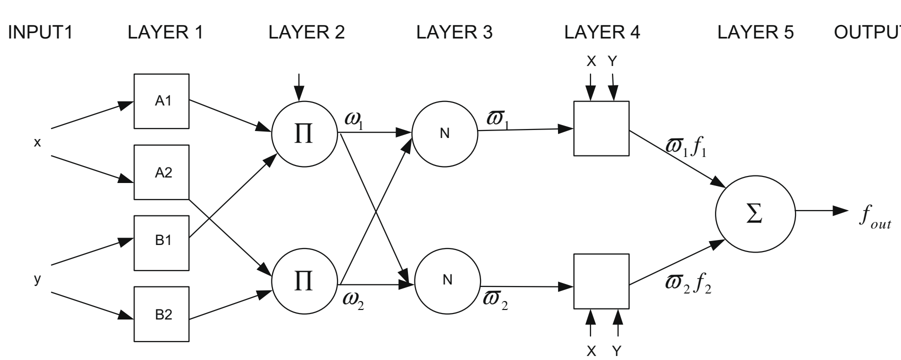

Fig. 1. The framework of an ANFIS.

where $\boldsymbol{\theta}$ is an unknown matrix, whose elements come from the consequent parameters set. The least squares estimator(LSE) $\boldsymbol{\theta}^*$ is given by

$$\boldsymbol{\theta}^* = (B^T B)^{-1} B^T f \tag{13}$$

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 $\mathbf{B}$ and $\boldsymbol{f}$ 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 $\partial E_i/\partial O$ for the ith entry of the training data set and for each node output O. If α is a parameter of the premise parameters set, by the chain rule, the derivative of the overall error measure E with respect to α is

$$\frac{\partial E}{\partial \alpha} = \sum_{i=1}^{n} \frac{\partial E_i}{\partial \alpha} = \sum_{i=1}^{n} \sum_{\widetilde{O} \in V} \frac{\partial E_i}{\partial \widetilde{O}} \frac{\partial \widetilde{O}}{\partial \alpha} \tag{14}$$

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

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{15}$$

in which η 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).

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	24320
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

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.

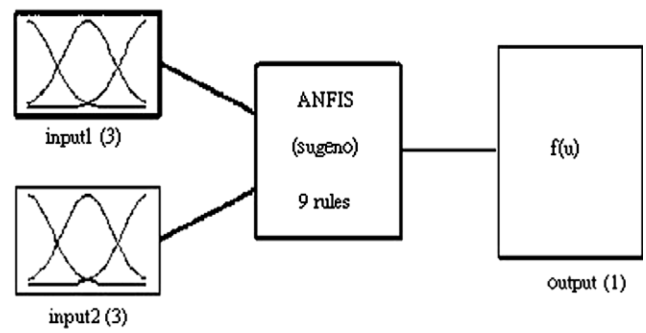

Fig. 2. Fuzzy rule architecture of the ANFIS. System ANFIS: two inputs, one output, and nine rules.

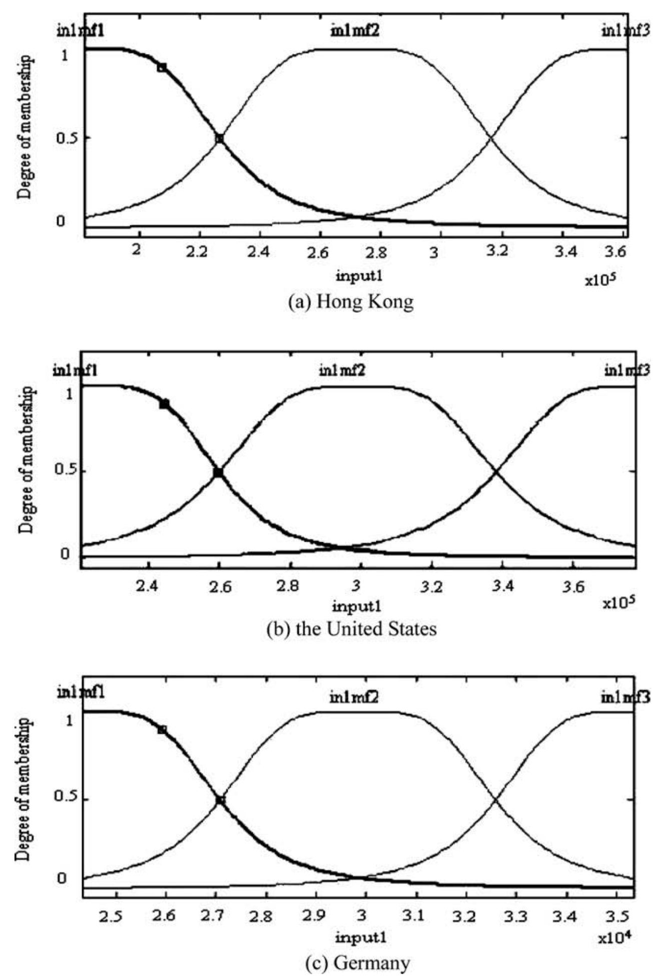

Fig. 3. Initial bell shaped membership functions of the three markets.

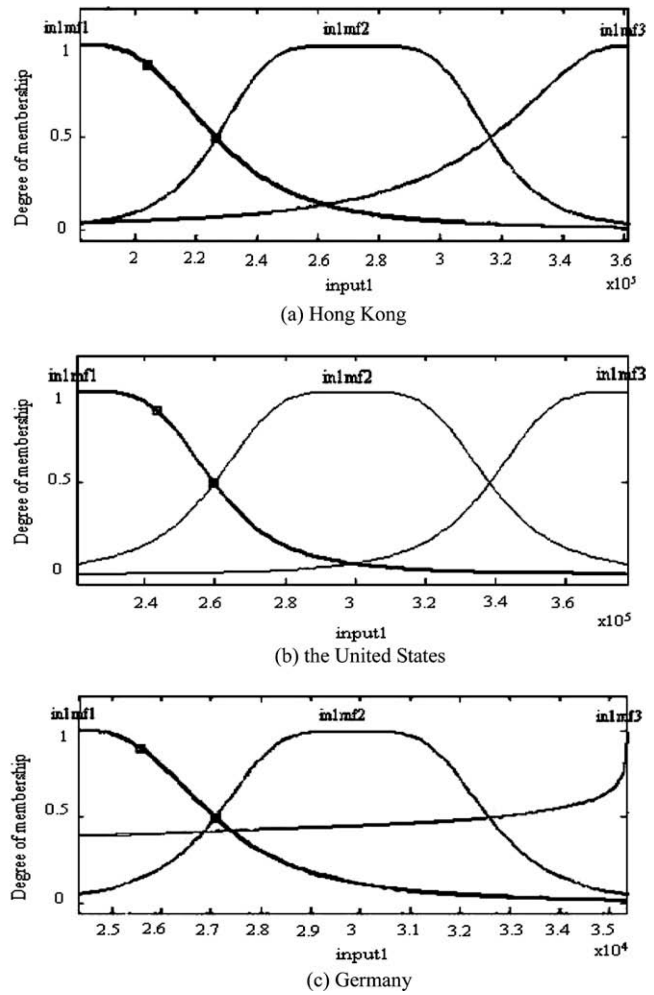

Fig. 4. Final membership functions of the three markets.

$$\mathrm{APE} = \left|\frac{t_i - m_i}{t_i}\right| \times 100\% \tag{16}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - m_i}{t_i}\right| \times 100\% \tag{17}$$

where t_i and m_i represent the actual and forecasted values of the ith data, respectively, and N is the number of data.

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–Smimov (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 ($\overline{D}$), 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	–	–	25921	24580	–
1991	181708	195121	182970		239782	239144	246140	–	25802	26793	25433	–
1992	193875	208850	196183		259901	248275	255673	–	28965	27694	29073	–
1993	213598	223546	210340		268507	257754	265577	–	28645	28626	30024	–
1994	241738	239276	253044		289648	267595	275868	283557	31333	29589	31007	–
1995	247251	256113	241759		286570	277812	286560	301160	32942	30584	32022	–
1996	261944	274134	259170	258367	293808	288420	297970	298285	33926	31613	33071	–
1997	259824	293424	277822	274205	294904	299432	309213	291747	34745	32677	34155	34919
1998	280031	314071	297805	264484	311326	310864	300521	318081	34506	33776	35275	35665
1999	319755	336170	319213	305125	330341	322733	311796	310254	34155	34913	33393	36348
2000	361314	325925	377504	351834	349375	335056	346622	332248	34899	36087	34546	33860
MAPE (%)	0.0969	6.9094	2.9768	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
	$\overline{D}$	−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
	$\overline{D}$	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
	$\overline{D}$	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)	400128(1.93)	393232(0.1732)	456295(0.0567)	434692(34.505)
The United States	347848(0.275)	360079(3.231)	386580(10.83)	349153(0.0989)	377789(0.0845)	369814(35.534)
Germany	37301(10.634)	35739(6.000)	35834(6.28)	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	–	25738	–
	March	109459	107644	34443	34554	33655	33530
	April	84425	85519	42018	42090	32584	33570
	May	90886	92121	35820	36415	32702	33004
	June	91676	91785	39995	41120	40492	39507
	July	81029	80188	38126	43538	36019	35888
	August	98725	96527	44668	44070	29550	29681
	September	102438	103709	32095	30681	26231	26396
	October	103465	99863	28029	27791	34341	34201
	November	114547	115002	28383	28582	34766	34005
	December	99810	99979	41769	41726	37476	38221
2007							
	January	101563	102306	23879	23658	27712	27761
	February	84736	97985	35289	35291	28892	28594
	March	120599	120650	36283	36434	36044	36071
	April	89021	89581	49732	48947	32199	32405
	May	90784	90304	39057	38911	31551	32219
	June	92127	92228	49526	48968	38982	40250
	July	81116	83637	42788	43588	36351	36681
	August	97795	101001	49586	49888	29970	30055
	September	101584	102646	37729	37914	27100	27035
	October	99419	94768	36549	37111	35495	36601
	November	106875	108529	38047	41370	33668	33666
	December	100761	101104	52972	46894	40001	39561
2008							
	January	98392	96756	30088	30143	30092	30267
	February	92394	93371	50024	50106	27584	27749
	March	106520	106867	56303	56426	38350	37678
	April	82136	82537	43224	43245	31478	31531
	MAPE (%)		1.82236		2.16596		1.10851

(L), and width (W) of the 95% confidence interval of $\overline{D}$ for the different markets.

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 ($\overline{D}$) and the 95% confidence interval estimate of the mean difference $\overline{D}$ of matched data, we can see that the values of $\overline{D}$ of the ANFIS model are very close to zero and the widths of the 95% confidence interval of $\overline{D}$ 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.

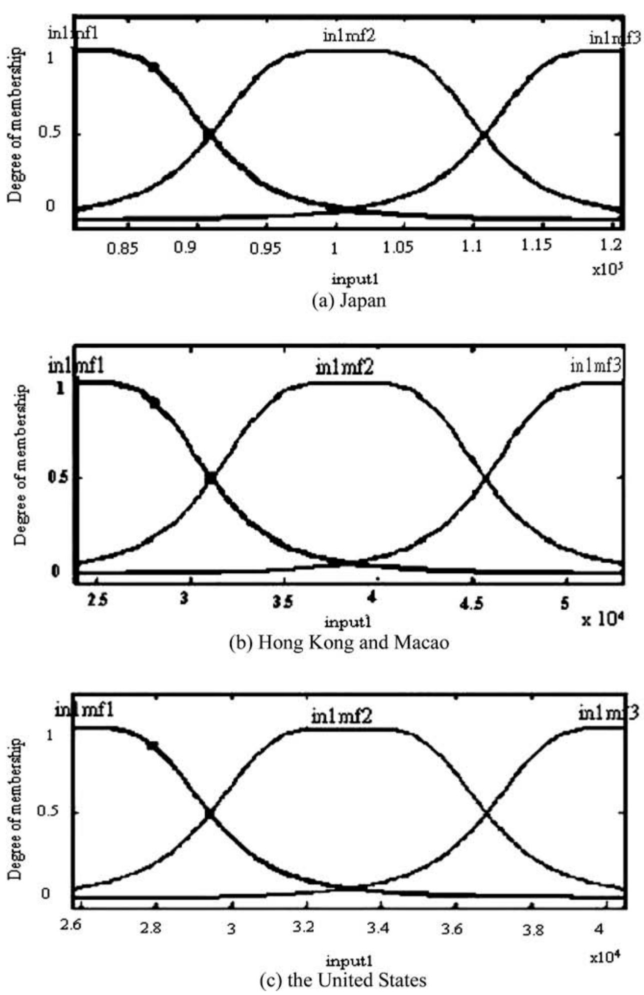

Fig. 5. Initial bell shaped membership functions of the top three markets.

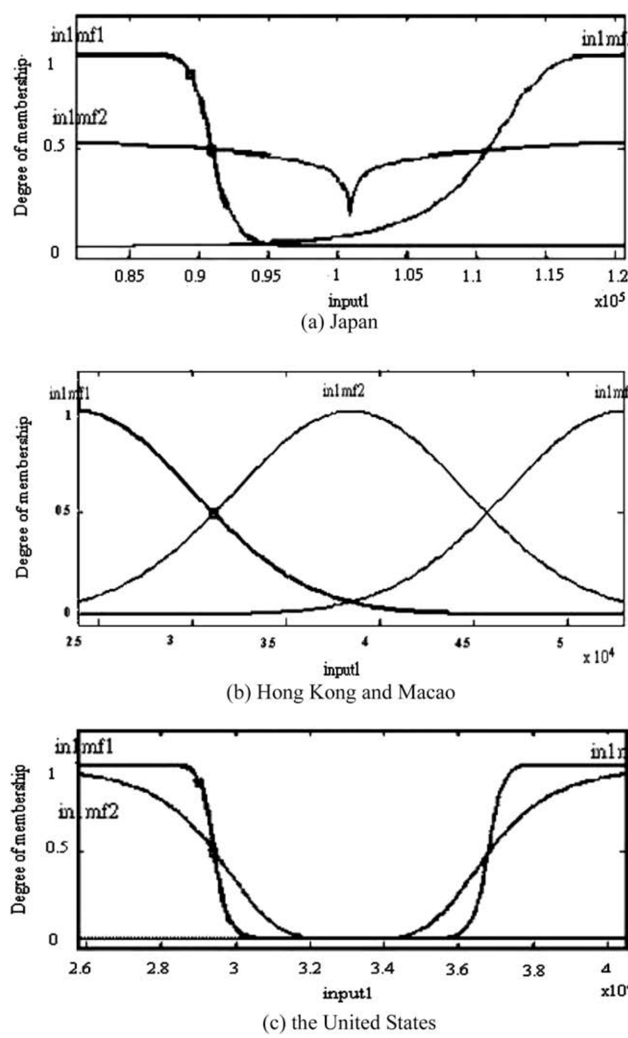

Fig. 6. Final membership functions of the top three markets.

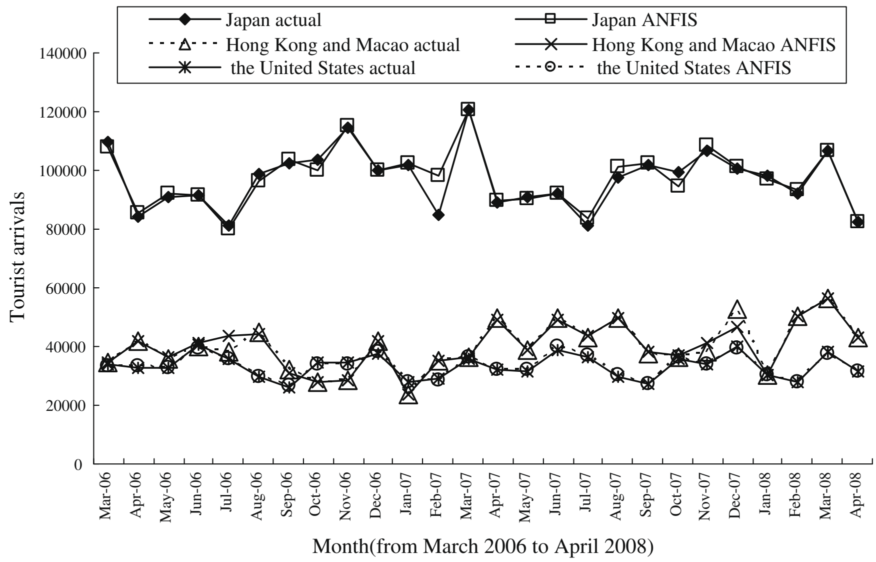

Fig. 7. Actual values and the ANFIS forecasting values for monthly tourist arrivals to Taiwan from top three markets.

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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