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Case Study

Tourist arrival forecasting by evolutionary fuzzy systems

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ABSTRACT

Accurate forecasts of tourist arrivals and study of the tourist arrival patterns are essential for the tourism-related industries to formulate efficient and effective strategies on maintaining and boosting tourism industry in a country. Forecasting accuracy is one of the most important factors involved in selecting a forecasting method. This study presents a hybrid artificial intelligence (AI) model to develop a Mamdani-type fuzzy rule-based system to forecast tourist arrivals with high accuracy. The hybrid model uses genetic algorithm for learning rule base and tuning data base of fuzzy system. Actually it extracts useful information patterns with a descriptive rule induction approach based on Genetic Fuzzy Systems (GFS). This is the first study on using a GFS with the ability of learning rule base and tuning data base of fuzzy system for tourist arrival forecasting problem. Evaluation of the proposed approach will be carried out by applying it to a case study of tourist arrivals to Taiwan and results will be compared with other studies which have used the same data set. Results show that the proposed approach has high accuracy, so it can be considered as a suitable tool for tourism arrival forecasting problems.

1. Introduction and literature review

Forecasting is the process of making projections about future performance based on existing historic data. An accurate forecast aids in decision-making and planning for the future. Forecasts empower people to modify current variables at the present time to predict the future in order to attain a favorable scenario.

Without a doubt, forecasting is a crucial issue particularly in the tourism industry. As described by Dharmaratne (1995), many tourism products like hotel rooms, airline seats and car rentals have a perishable nature. Unfilled rooms and airline seats cannot be inventoried. Tourism demand must be forecasted.

Accurate forecasts on tourism demand and study on the pattern of the tourism demand from various origins are essential for the tourism-related industries to formulate efficient and effective strategies on maintaining and boosting tourism industry in a country. With the forecasted trend and pattern on the coming tourism demand, the government can have a well-organized tourism strategy and provide a better infrastructure to serve the visitors; while for the private sector, they can develop a suitable marketing strategy to get the benefit from the growing tourism. Therefore, it is vital to forecast tourism demand for a country. In the past few decades, there was a great development in the study of tourism demand, a large number of empirical studies have been published.

The most commonly used tourism demand forecasting techniques are time-series models such as ARIMA and GARCH (Alleyne, 2006; Gil-Alana, Gracia, & Cunado, 2004; Lee, Song, & Mjelde, 2008; Lim & McAleer, 2002) and econometric models such as error correction model (ECM) and the vector autoregressive (VAR) models (Song & Witt, 2006; Wong, Song, Witt, & Wu, 2007). These models use piecewise linear function as basic elements of prediction model. The functional form for the problem has to be specified by users. It could take a lot of time to experiment with the different possible function relations and algorithms to obtain proper models.

Artificial Intelligence techniques such as artificial neural networks (ANNs), fuzzy logic, and genetic algorithms (GAs) are popular techniques to solve the complex engineering and optimization problems (Konar, 2005). These models have more flexibility and can be used to estimate the non-linear relationship, without the limits of traditional Time Series and econometric models. Therefore, more and more researchers tend to use AI forecasting models to deal with problems. These AI techniques have been applied to tourist arrivals forecasting in some of the recent studies. Empirical evidence shows AI models generally outperform the

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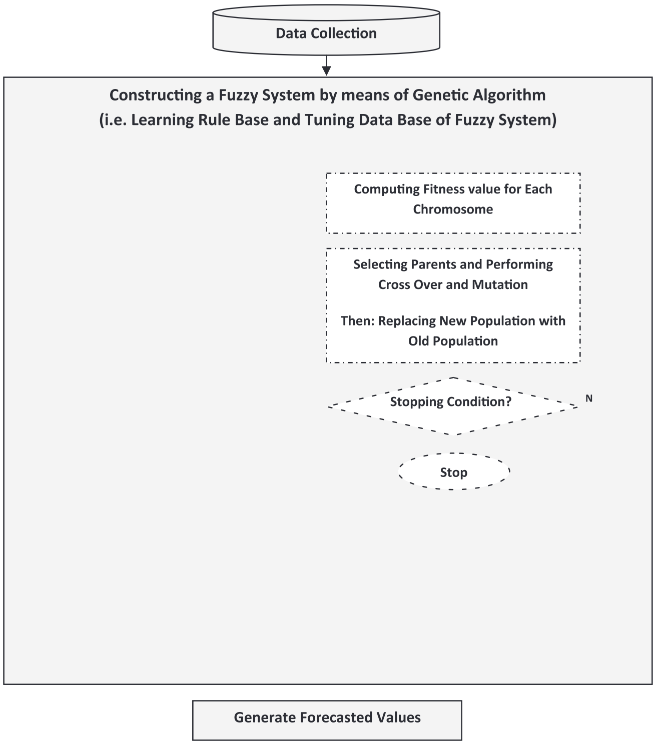

classical time-series and econometric models in tourism forecasting.

Cho (2003) Compared the application of three time-series forecasting techniques, namely exponential smoothing, univariate ARIMA, and Elman's Model of Artificial Neural Networks (ANN), to predict travel demand (i.e. the number of arrivals) from different countries to Hong Kong. According to the analysis presented in this paper, Neural Networks seems to be the best method for forecasting visitor arrivals, especially those series without obvious patterns.

Kon and Turner (2005) provided a review of the applications of ANN methods in tourism demand forecasting. Empirical evidence shows that ANNs generally outperform the classical time-series and multiple regression models in tourism forecasting.

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. Experimental results showed that 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.

Each of the AI-based techniques has advantages and disadvantages. One approach to deal with complex real-world problems is to integrate the use of several AI technologies in order to combine their different strengths and overcome a single technology's weakness to generate hybrid models that provide better results than the ones achieved with the use of each isolated technique. Therefore, more and more researchers tend to use hybrid forecasting models to deal with forecasting problems in various fields. In spite of this fact, there are few studies in literature concerned with applying hybrid models on tourism demand forecasting problems (a complete literature review on proposed techniques for tourism demand modeling can be found in (Song & Lib, 2008)).

Pai, Hong, Chang, and Chen (2006) proposed a support vector machine (SVM) approach by means of GAs for tourist demand forecasting in Barbados. Empirical evidences showed that the hybrid model was superior to AIRMA.

Chen, Ying, and Pan (2009) used adaptive network-based fuzzy inference system (ANFIS) model to forecast the tourist arrivals to Taiwan and demonstrated the forecasting performance of this model. Experimental results showed that the ANFIS model has better forecasting performance than the fuzzy time-series model, grey forecasting model and Markov residual modified model proposed by Wang (2004).

One of the most popular approaches is the hybridization between fuzzy logic and GAs leading to genetic fuzzy systems (GFSs) (Cordón, Herrera, Hoffmann, & Magdalena, 2001). A GFS is basically a fuzzy system augmented by a learning process based on evolutionary computation, which includes genetic algorithms and other evolutionary algorithms (EAs) (Eiben & Smith, 2003; Hadavandi, Shavandi, & Ghanbari, 2010).

In recent years some articles have been published in favor of using GFSs in behavior modeling area (Casillas & Martínez-López, 2009; Martínez-López & Casillas, 2009; Orriols-Puig, Casillas, & Martínez-López, 2009). They have all obtained satisfactory results and concluded that using GFSs is very promising for this area, in spite of this fact, there is not any research in the literature that uses a GFS with the ability of learning rule base and tuning data base of fuzzy system for tourist arrival forecasting problem.

This paper presents a hybrid artificial intelligence model to developing a Mamdani-type fuzzy rule-based system to forecast monthly tourist arrivals to Taiwan from the top three markets. The hybrid model uses genetic algorithm for learning rule base and tuning data base of fuzzy system and extracts useful patterns of information with a descriptive rule induction approach based on Genetic Fuzzy Systems. The evaluation process is carried out by means of the same data set which is used in (Chen et al., 2009; Wang, 2004).

2. Methodology

2.1. Developing a genetic fuzzy system

Nowadays fuzzy rule-based systems are successfully applied to a wide range of real-world problems from different areas. In order to design an intelligent system of this kind for a concrete

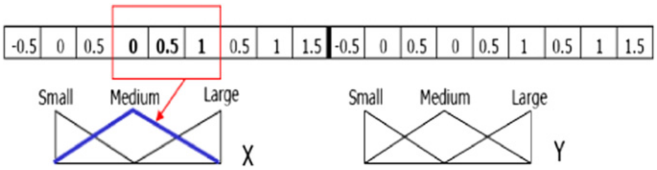

Fig. 3. Coding data base as chromosomes.

application, several tasks have to be performed. One of the most important and difficult ones is to derive an appropriate knowledge base (KB) about the problem. The KB stores the available knowledge in the form of fuzzy linguistic IF– THEN rules. It is composed of the rule base (RB), constituted by the collection of rules in their symbolic forms, and the data base (DB), which contains the linguistic term sets and the membership functions defining their meanings (Casillas, Cordón, Herrera, & Villar, 2004)

The difficulty presented by human experts to express their knowledge in the form of fuzzy rules has made researchers develop automatic techniques to perform this task. In this sense, a large amount of methods has been proposed to automatically generate fuzzy rules from numerical data. Usually, they use complex rule generation mechanisms such as neural networks (Nauck, Klawonn, & Kruse, 1997) or genetic algorithms (Cordón, Herrera, Hoffmann, & Magdalena, 2001)

GAs have been demonstrated to be a powerful tool for automating the definition of the KB, since adaptive control, learning, and self-organization may be considered in a lot of cases as optimization or search processes. In particular, the application to the design, learning, and tuning of KBs has produced quite promising results. These approaches can be given the general name of genetic fuzzy systems (Cordon & Herrera, 1995).

In this paper we use a Mamdani-type fuzzy rule-based system (FRBS) to deal with tourist arrivals forecasting problem. In a Mamdani-type FRBS a common rule is represented as follows:

IF X_1 is A_1 and X_2 is A_2 THEN Y is C_1, where X_1, X_2 and Y are linguistic variables and A_1, A_2 and $C_1$are corresponding fuzzy sets. Evolutionary process that we use in this paper for evolving knowledge base of FRBS consists of two general stages; stage 1 learns rule base of FRBS and stage 2 tunes data base of FRBS. In the following we'll describe theses two stages. General framework of the proposed model for constructing FRBS is shown in Fig. 1

2.2. *Genetic learning of the rule base*

A previously defined DB constituted by uniform fuzzy partitions with triangular membership functions crossing at height 0.5 is considered. The number of linguistic terms forming each one of them can be specified by the GFS designer, and then Pittsburgh approach (Smith, 1980) is used for learning RB. Each chromosome encodes a whole fuzzy rule set and the derived RB is the best individual of the last population. Pittsburgh approach can be decomposed in the following steps.

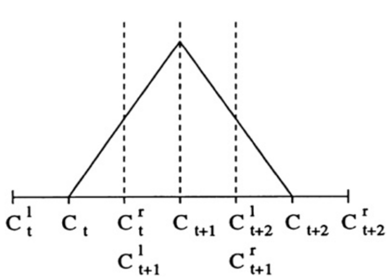

Fig. 4. Membership function and performance interval for the tuning process.

Table 1
Suitable GFS features for each region.

Parameter(s)	Region		
	Hong Kong	Germany	United States
Number of labels	5	5	4
Population size	100	70	100
Number of generations	1000	1000	800
Crossover probability	0.75	0.75	0.6
Mutation probability	0.01	0.01	0.04

Step 1 Coding mechanism

Many GFSs employ the decision table proposed by Thrift (Thrift, 1991) as the common classical representation for the RB of an FRBS. A fuzzy decision table represents a special case of a crisp relation (the ordinary type of relations we are familiar with) defined over the collections of fuzzy sets corresponding to the input and output variables. A chromosome is obtained from the decision table by going row-wise and coding each output fuzzy set as an integer number with start from 1 to number of output variable linguistic terms. Fuzzy decision table for an FRBS with two inputs (X_1,X_2) and one output (Y) variable, with three fuzzy sets (A_{11},A_{12},A_{13},A_{21},A_{22},A_{23}) related to each input variable and four fuzzy sets (B_1,B_2,B_3,B_4) related to the output variable and applying this code to the fuzzy decision table represented in Fig. 2.

Step 2 Generating the initial population

Initial chromosomes (N_{pop}) are randomly generated; while the alleles are in the set {1,2,...,N_B} (N_B is the number of output variables' linguistic terms). All consequent labels have the same probability to be assigned to each gene.

Step 3 Calculating the fitness values

As regards the fitness function, it is based on an application-specific measure usually employed in the design of GFSs, the mean squared error (MSE) over a training data set, which is represented by the following expression:

Table 2
Forecasted values vs. actual values.

Year	Hong Kong		USA		Germany	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
1991	181,765	183,793	240,375	241,135	25,798	25,794
1992	193,523	192,843	259,145	256,360	28,969	28,955.93
1993	213,953	212,056	269,110	268,906	28,644	28,607
1994	241,775	244,810	286,713	285,528	31,334	31,335
1995	246,747	246,015	290,138	291,781	32,944	32,964
1996	262,585	261,622	289,900	291,298	33,914	33,913
1997	259,664	259,046	303,634	301,868	34,660	34,687
1998	279,905	278,504	308,407	307,750	35,343	35,387
1999	319,814	317,024	317,801	320,207	34,190	34,267
2000	361,308	359,928	359,533	362,060	34,829	34,721
2001	392,552	397,753	348,808	350,839	33,716	34,568
2002	456,554	400,637	377,470	371,018	33,979	33,987
2003	323,178	314,646	272,858	338,702	28,577	34,889

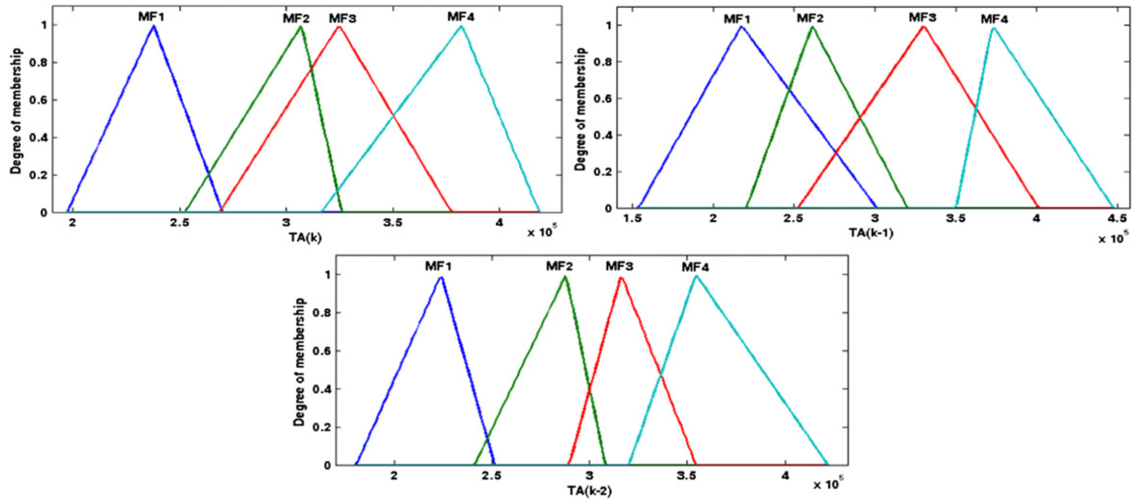

Fig. 5. Tuned membership functions (for USA).

$$\mathrm{MSE}(C_j) = \frac{1}{N}\sum_{i=1}^{N}(Y_i - P_i)^2$$

where Y_i is the actual value and P_i is the output value of ith training data obtained from the FRBS using the RB coded in jth chromosome (C_j and N is the number of training data.

Step 4 Generate $(N_{\mathrm{pop}} - 1)$ chromosome using the genetic operations

We use binary tournament selection scheme for selection procedure. In binary tournament selection, two members of the population are selected at random and their fitness compared and the best one according to fitness value will be chosen to reproduce. Also we use one-point crossover and uniform mutation for genetic operators.

Step 5 Add the best rule set in the current population to the newly generated $(N_{\mathrm{pop}} - 1)$ chromosome to form the next population.

Step 6 If the number of generations equals to the maximum generation number, then stop; otherwise go to *step 3*.

2.3. Genetic tuning of data base

After generation of rule base, we utilize the genetic tuning process that was proposed by Cordón and Herrera (1997). This tuning process slightly adjusts the shape of the membership functions of a preliminary DB defined. This approach can be decomposed in the following steps.

Step 1 Coding data base as chromosomes

Each chromosome encodes a different DB definition. We use triangular membership functions for input and output variables' linguistic terms. Each triangular membership function is encoded by 3 real values, a primary fuzzy partition is represented as an array composed of 3N real values, with N being the number of linguistic terms for each variable (we take the same number of linguistic terms for each input and output linguistic variable). The complete DB for a problem, in which M linguistic variables are involved, is encoded into a fixed-length real coded chromosome C_j built by joining the partial representations of each one of variable fuzzy partitions as is shown in the following:

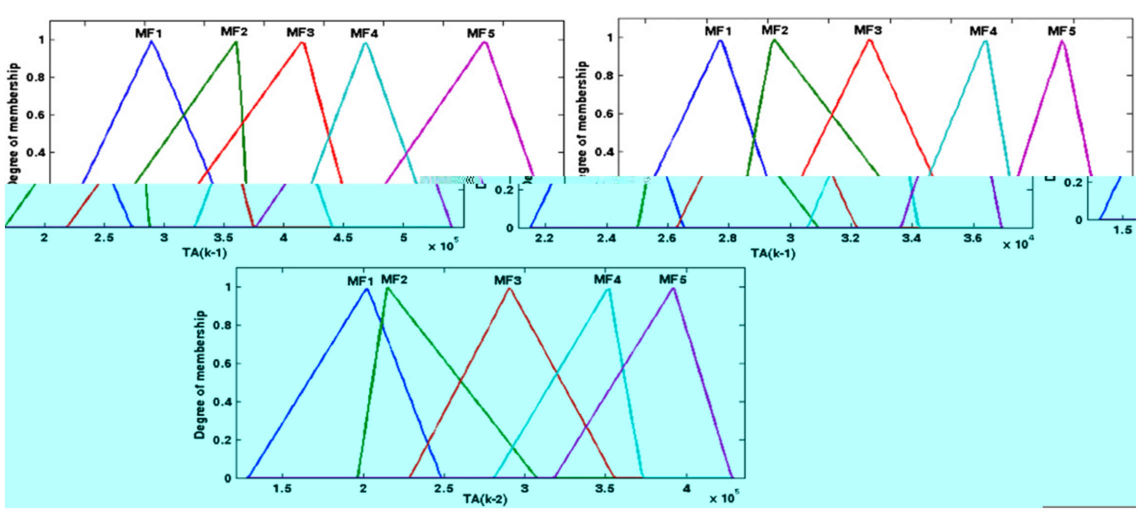

Fig. 6. Tuned membership functions (for Hong Kong).

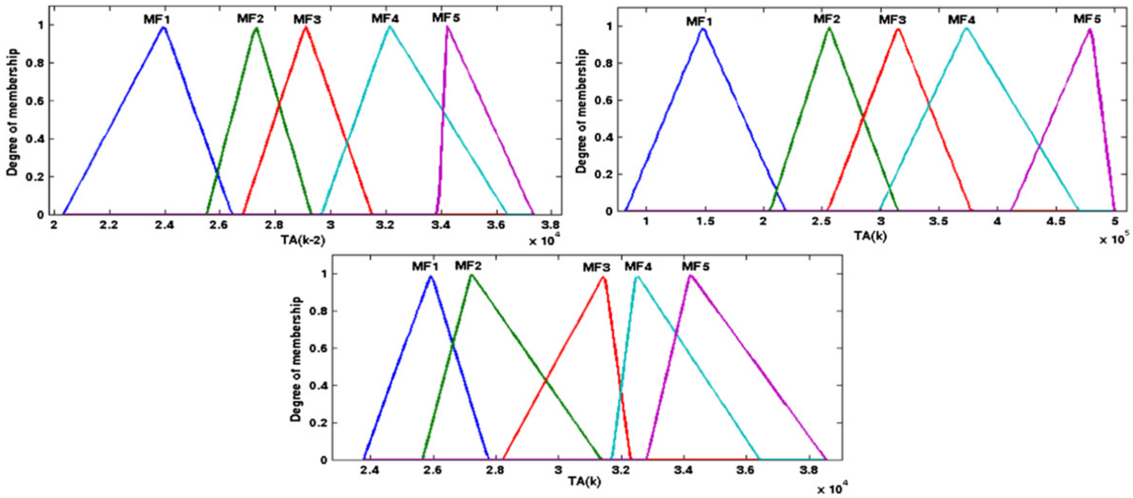

Fig. 7. Tuned membership functions (for Germany).

$$C_i^j = \left(a_{i1}^j, b_{i1}^j, c_{i1}^j, a_{i2}^j, b_{i2}^j, c_{i2}^j, \ldots, a_{iN}^j, b_{iN}^j, c_{iN}^j\right)$$

$$C_j = C_1^j C_2^j C_3^j \ldots C_{M-1}^j C_m^j$$

A sample coded data base with one input variable as well as one output variable was shown in Fig. 3. Each variable is defined by a fuzzy linguistic term such as small, medium, and large.

Step 2 Generating the initial population

The initial population (N_{pop}) is created by using the initial DB definition. The first chromosome (C_1) is encoded directly from initial DB definition. The remaining individuals ($N_{\text{pop}} - 1$) are generated by associating an interval of performance, $[c_h^l, c_h^r]$ to every gene c_h in $C_1, h = 1,2,\ldots,3NM$. Each interval of performance will be the interval of adjustment for the corresponding variable, $c_h \varepsilon [c_h^l, c_h^r]$.

If $t \bmod 3 = 1$ then c_t is the left value of the support of a triangular fuzzy number. The triangular fuzzy number is defined by the three parameters (c_t,c_{t+1},c_{t+2}) and the intervals of performance are as the following:

$$c_t \varepsilon \left[c_t^l, c_t^r\right] = \left[c_t - \frac{c_{t+1} - c_t}{2}, c_t + \frac{c_{t+1} - c_t}{2}\right]$$

$$c_{t+1} \varepsilon \left[c_{t+1}^l, c_{t+1}^r\right] = \left[c_{t+1} - \frac{c_{t+1} - c_t}{2}, c_{t+1} + \frac{c_{t+2} - c_{t+1}}{2}\right]$$

$$c_{t+2} \varepsilon \left[c_{t+2}^l, c_{t+2}^r\right] = \left[c_{t+2} - \frac{c_{t+2} - c_{t+1}}{2}, c_{t+2} + \frac{c_{t+3} - c_{t+2}}{2}\right]$$

Fig. 4 shows these intervals.

Step 3 Fitness value function

We use MSE over a training data set as fitness function. This fitness function is applied on the chromosomes considering the tuned membership functions and the rule base extracted in previous phase.

a

TA(k-1) \ TA(k-2)	MF1	MF2	MF3	MF4	MF5
MF1	MF1	MF2	MF1	MF4	MF1
MF2	MF3	MF1	MF3	MF1	MF2
MF3	MF2	MF2	MF4	MF1	MF3
MF4	MF3	MF4	MF5	MF4	MF4
MF5	MF1	MF5	MF1	MF5	MF4

b

TA(k-1) \ TA(k-2)	MF1	MF2	MF3	MF4	MF5
MF1	MF1	MF1	MF5	MF1	MF3
MF2	MF4	MF1	MF3	MF5	
MF3	MF5	MF3	MF4	MF3	
MF4	MF5	MF2	MF4	MF5	
MF5	MF1	MF1	MF3	MF1	

c

TA(k-1) \ TA(k-2)	MF1	MF2	MF3	MF4
MF1	MF1	MF2	MF4	MF1
MF2	MF2	MF1	MF1	MF3
MF3	MF3	MF4	MF4	MF4
MF4	MF3	MF2	MF3	MF3

Fig. 8. Rule base of GFS: (a) Germany (b) Hong Kong (c) USA.

Table 3
Comparison of the approaches (train data).

Region	GFS	ANFIS	GM(1,1)	Markov	Fuzzy ($w = 5$)
Hong Kong	0.6265	0.0969	6.9094	2.9768	3.9862
USA	0.51824	1.4957	3.0894	2.2725	3.5439
Germany	0.0996	0.2992	4.372	1.7713	2.6881

Table 4
Comparison of GFS and ANFIS (test data).

Region	GFS	ANFIS
Hong Kong	5.404193044	11.5783
USA	8.807	11.9058
Germany	8.212358848	7.42036

Table 5
Suitable GFS features for each region.

GFS-suitable features	Hong Kong and Macao	Japan	United States
Number of labels	6	6	6
Population size	60	78	60
Number of generations	2200	2908	2755
Cross probability	0.87	0.87	0.87
Mutation probability	0.01	0.01	0.01

Step 4 Selection and elitism

The best ten percent of the population are copied without changes in the elitism set. Elitism set ensures that the best chromosomes will not be destroyed during crossover and mutation. The selection process is then implemented. We use binary tournament selection scheme to selecting chromosomes for mating pool. The size of the mating pool equals ninety percent of the population size.

Step 5 Genetic operators

We use $BLX - 0.1$ crossover (Eshelman & Schaffer, 1993) and uniform mutation in the proposed genetic tuning process.

Step 6 Replacement

The current population is replaced by the newly generated offsprings, which forms the next generation by integrating the elitism set.

Step 7 Stopping criteria

If the number of generations equals to the maximum generation number, then stop; otherwise go to *step 3*.

3. Experimental results

In this section, we develop the proposed GFS by means of the same data set which is used by Wang (2004) and Chen et al. (2009). We employ the annual tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany, from 1989 to 2003 as our research data. The data set is divided into two data sets: the training data set (from 1989 to 2000) and the testing data set (from 2001 to 2003). Tourist arrivals forecasting, in terms of input, will be addressed using time lags of tourist arrivals. We use 2 lags of tourist arrivals as input variables (i.e. same input variables which were employed by Chen et al. (2009)). So, the proposed GFS model is used for a projecting/reflecting action:

$$f : (TA(k-1), TA(k-2)) \rightarrow TA(k)$$

where $TA(k)$ is tourist arrivals to Taiwan in kth year from a destination.

Table 6
Predictions of ANFIS and GFS.

Year		Japan			Hong Kong and Maccao			USA		
		Actual	ANFIS	GFS	Actual	ANFIS	GFS	Actual	ANFIS	GFS
2006	January	85,523						31,248		
	February	99,506			34,124			25,738		
	March	10,9459	107,644	113,149	34,443	34,554	34,693	33,655	33,530	33,801
	April	84,425	85,519	84,237	42,018	42,090	41,561	32,584	33,570	32,997
	May	90,886	92,121	92,028	35,820	36,415	35,765	32,702	33,004	32,745
	June	91,676	91,785	91,904	39,995	41,120	38,778	40,492	39,507	40,159
	July	81,029	80,188	82,502	38,126	43,538	36,759	36,019	35,888	36,281
	August	98,725	96,527	98,017	44,668	44,070	43,992	29,550	29,681	29,912
	September	102,438	103,709	103,777	32,095	30,681	31,664	26,231	26,396	26,087
	October	103,465	99,863	100,350	28,029	27,791	27,419	34,341	34,201	33,980
	November	114,547	115,002	113,649	28,383	28,582	28,245	34,766	34,005	34,358
	December	99,810	99,979	99,819	41,769	41,726	41,068	37,476	38,221	37,451
2007	January	101,563	102,306	101/609	23,879	23,658	24,214	27,712	27,761	27,694
	February	84,736	97,985	88/867	35,289	35,291	35,825	28,892	28,594	28,520
	March	120,599	120,650	118/050	36,283	36,434	36,227	36,044	36,071	36,376
	April	89,021	89,581	90/211	49,732	48,947	49,771	32,199	32,405	32,339
	May	90,784	90,304	92,226	39,057	38,911	40,122	31,551	32,219	31,361
	June	92,127	92,228	90,112	49,526	48,968	46,893	38,982	40,250	39,151
	July	81,116	83,637	81,074	42,788	43,588	41,876	36,351	36,681	36,191
	August	97,795	101,001	97,620	49,586	49,888	50,321	29,970	30,055	30,135
	September	101,584	102,646	103,768	37,729	37,914	38,565	27,100	27,035	27,379
	October	99,419	94,768	96,273	36,549	37,111	37,403	35,495	36,601	35,876
	November	106,875	108,529	108,008	38,047	41,370	39,290	33,668	33,666	33,449
	December	100,761	101,104	100,625	52,972	46,894	53,516	40,001	39,561	40,234
2008	January	98,392	96,756	100,079	30,088	30,143	30,295	30,092	30,267	29,931
	February	92,394	93,371	91,772	50,024	50,106	50,998	27,584	27,749	27,717
	March	106,520	106,867	106,857	56,303	56,426	55,667	38,350	37,678	37,987
	April	82,136	82,537	81,244	43,224	43,245	43,792	31,478	31,531	31,484
	MAPE (%)		1.853	1.362		2.16596	1.712		1.1085	0.6726

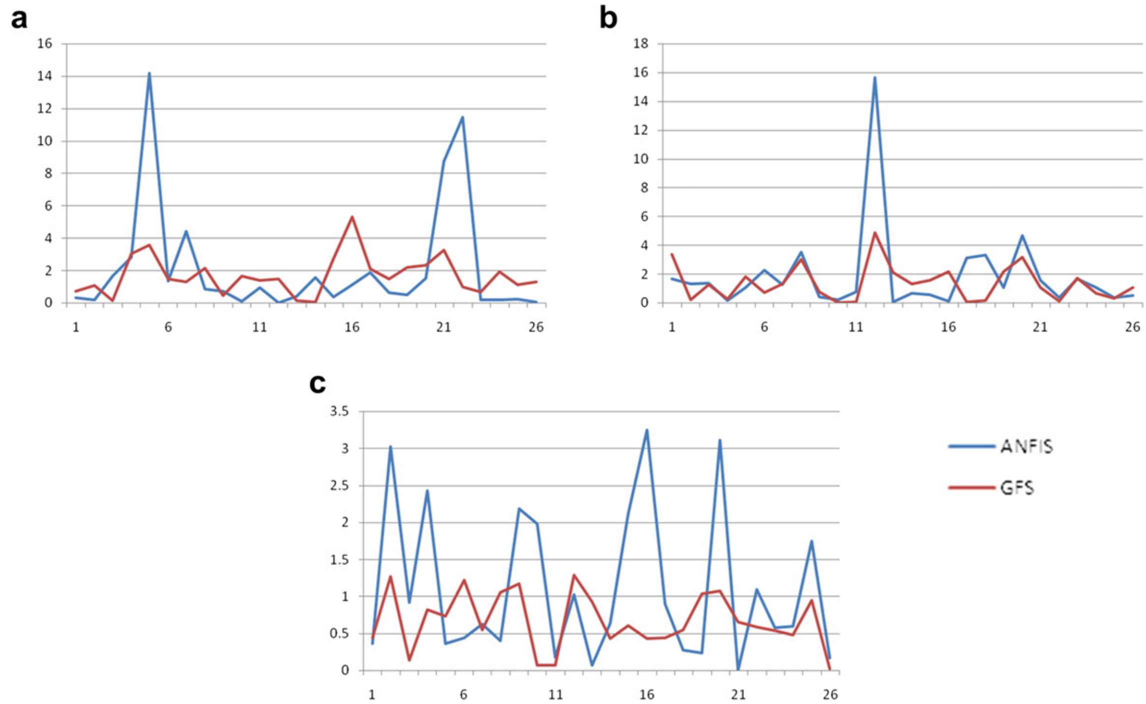

Fig 9. APE of predictions: (a) Hong Kong and Maccao (b) Japan (c) USA.

3.1. Constructing GFS for tourist arrivals forecasting

In this section we build a GFS to forecast tourist arrivals to Taiwan using the training data set for each origin. The suitable features of GFSs for each origin after examination of different values are shown in Table 1.

The forecasting results of the proposed model for different markets are listed in Table 2. Also the tuned membership functions of input and output variables (for each origin) are shown in Figs. 5–7 respectively. Also rule base of each GFS is shown in Fig. 8.

3.2. Comparisons of proposed GFS with other models in literature

For the purpose of evaluating GFS's forecasting accuracy, we will compare outputs of this method with other methods that are proposed for forecasting annual tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany. We perform this task by a common evaluation statistic called MAPE:

$$\mathrm{MAPE} = 100 \times \frac{1}{N} \sum_{i=1}^{N} \frac{|Y_i - P_i|}{Y_i}$$

where Y_i is actual value and P_i is the forecasted value of ith train/test data obtained from GFS model and N is number of train/test data. Summary of GFS evaluations in comparison with the other methods for training data is shown in Table 3.

The GFS model has smaller MAPE values than the ANFIS proposed by Chen et al. (2009) for the tourism demand forecasting of Germany and the United States arrivals, and fuzzy time-series, grey forecasting model GM(1,1) and Markov residual modified model proposed by Wang (2004). So the GFS model seems to be more accurate than all the other models. We use the GFS model to forecast tourist arrivals to Taiwan from the three markets: Hong Kong, the United States and Germany from 2001 to 2003. Summary of GFS evaluations in comparison with the ANFIS model based on MAPE value is shown in Table 4.

3.3. Forecasting of the monthly tourist arrivals from the top three market

According to the comparative results shown in the previous section, it could be concluded that the GFS model is relatively better than the others. We apply the GFS 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, then we compare the results with ANFIS model proposed by Chen et al. (2009). The suitable features of GFSs for each origin after examination of different values are shown in Table 5.

The forecasting results of the GFS model for the different markets are listed in Table 6. Also, absolute percentage errors (APE) of ANFIS and GFS models are shown in Fig 9.

Regarding Table 6, the proposed GFS model has improved the forecasting accuracy of monthly tourist arrivals to Taiwan from Japan, Hong Kong and Macao, and the United States. Besides, also Fig. 9 shows that forecasts of GFS model are more stable than ANFIS, because the GFS's variance of errors are lower than that of ANFIS. We use Levene's test (Levene, 1960) for proving this hypothesis and checking homogeneity of error variances of forecasting values for each origin (Detailed procedure of Levene's test is described in Appendix A). As it's shown in Table 7, differences between error

Table 7
Results of Levene's test.

Origin	Method	Average	Std-dev	Levenes's test		
Japan	GFS	1.362	1.23	Levene's *W*	*Df*	*p*-value
	ANFIS	1.853	3.05	1.7252	(1,50)	0.195
Hong Kong and Maccao	GFS	1.712	1.19	Levene's *W*	*Df*	*p*-value
	ANFIS	2.16596	3.64	7.0273	(1,50)	0.0107
USA	GFS	0.6726	0.3828	Levene's *W*	*Df*	*p*-value
	ANFIS	1.1085	1.019	21.644	(1,50)	0.000024

variances of forecasted values for "USA" and "Hong Kong and Maccao" origins are significant. Therefore, the GFS model can be considered as a promising alternative for tourism demand forecasting problems.

4. Conclusions

This paper presented a novel approach based on genetic fuzzy systems for building a tourism demand forecaster expert system, with the aim of improving forecasting accuracy. Proposed GFS approach has the following novel features:

- GAs have been demonstrated to be a powerful tool for automating the definition of the fuzzy rule-based systems. Proposed GFS uses genetic algorithms for extracting rule base of the fuzzy expert system.
- For the purpose of accuracy improvement, it tunes the data base of the expert system using a unique genetic algorithm.
- Moreover, policy makers are capable of handling non-linearity, complexity as well as uncertainty that may exist in actual data sets with respect to tourist arrivals due to erratic responses and measurement errors. The proposed model will provide policy makers with improved estimation and decreased error in complex and uncertain environment.
- We can be assured of working with optimum solutions, expressed in an easy, semantically understandable way of reasoning of the human being.

For the purpose of evaluating the proposed approach we applied it to tourist arrivals to Taiwan data which had been used in different papers as the case study. Results showed that forecasting accuracy of GFS is relatively better than other approaches regarding MAPE evaluation, and GFS can be used as a suitable forecasting tool in tourism demand forecasting problems.

Appendix A

Levene's test is used to test if K samples have equal variances. Given a variable Y with sample of size N divided into K subgroups, where N_i is the sample size of the ith subgroup, the Levene's test statistic is defined as:

$$W = \frac{(N-K)\sum_{i=1}^{k} N_i(\overline{Z}_{i.} - \overline{Z}_{..})^2}{(K-1)\sum_{i=2}^{N_i}(Z_{ij} - \overline{Z}_{i.})^2}$$

where

$$Z_{ij} = \left|Y_{ij} - \overline{Y}_1\right|$$

And $\overline{Y}_i$ is the mean of ith subgroup, $\overline{Z}_i$ are the group means of the Z_{ij} for ith subgroup and $\overline{Z}$ is the overall mean of the Z_{ij}. The Levene's test rejects the hypothesis that the variances are equal if

$$W > F(\alpha, K-1, N-K)$$

where $F(\alpha, K-1, N-K)$ is the upper critical value of the F distribution with $K-1$ and $N-K$ degrees of freedom at a significance level of α.

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