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Applying fuzzy logic of expert knowledge for accurate predictive algorithms of customer traffic flows in theme parks

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ABSTRACT

This study analyses two forecasting models based on the application of fuzzy logic and evaluates their effectiveness in predicting visitor expenditure and length of stay at a popular theme park. The forecasting models are based on a set of more than 600 decision rules constructed in the form of a complex series of IF-THEN statements. These algorithms store expert knowledge. A descriptive instrument that records the individual visitor's time spent and expenditure distribution on activities in the E-Da World in Taiwan was used to gather data. From a process of rigorous verification, the models developed are characterised by a high level of accuracy and efficiency.

Keywords: fuzzy logic, forecasting, theme park, customer behaviour, visitor expenditure, tourism management.

JEL classification: E37

1. Introduction

During the past decade, theme parks have enjoyed a significant growth in attendance. However, the future is less certain, as there are many factors shaping the prospects for theme parks that must be taken into account. For example, the increasing number of operators worldwide, new technology, rapid social and demographic changes, worldwide politics, and internal management problems are among the factors that will determine the survival of theme parks (Milman, 2010). In addition to these factors, theme park managers must consider the level of customer spending and the length of stay. Heo and Lee (2009) have determined that demographic attributes of customers relate directly to revenues, and therefore, they must always be considered in forecasting. Forecasting customer service consumption is also necessary because it relates to services offered, which affects spending and length of stay. The many techniques in the methodology of financial forecasting can be categorised into three types: (i) statistical, (ii) theoretical and (iii) computational intelligence. Korol (2012) and Aziz & Dar (2001) report that 64% of the case studies in finance use statistical forecasting, 25% use soft computing techniques and 11% use other types. Included under soft computing is artificial intelligence, which is becoming more important for successful business forecasting in the 21st century (Chiang, Chen, & Xu, 2007). However, forecasting is a very rare topic in theme park management literature. Some of the traditional techniques used include segmentation to forecast theme park revenue (Heo & Lee, 2009), cognitive appraisal theory to forecast the antecedents of emotions (Ma, Gao, Scott, & Ding, 2013), regression analysis to estimate service quality (Tsang, Lee, Wong, & Chong, 2012), multinomial logit model to predict the future impact of weather conditions (Joo, Kang, & Moon, 2012), structural equation modelling to investigate the connection between revisiting intention and theme park surroundings and shopping values (Chang, Shu, & King, 2014), and contingent valuation method to predict customers' willingness to pay (Lee, Graefe, & Hwang, 2013). It is interesting to note that only a few studies on theme park management use fuzzy logic, a type of artificial intelligence methodology (Tsaur & Kuo, 2011; Wang, 2004) and those that did dealt with service quality management rather than forecasting per se.

The objective of this research is to create two fuzzy logic models – the first to forecast the average level of customer spending in E-Da World and the second to predict the average length of visitor stay. It is necessary to note that the authors of this paper have not found any similar studies devoted to forecasting customer expenditure (Model 1) or the length of stay (Model 2) in a theme park setting. Modern economists cannot work without the mathematical apparatus. The economic model is a simplified reflection of reality that does not account for all of its aspects. In general, information of little importance is eliminated, which allows economists to focus on the essential features of economic reality. By using two models, theme park managers can maximise the usefulness of their actions (e.g., marketing activities). Based on a set of demographic factors, marketing decisions can be directed to improve the effectiveness and attractiveness of the theme park. For example, Model 1 forecasts consumer spending on particular activities (from 100 to more than 900 New Taiwanese Dollars - NTD per activity), which is subject to its demographic characteristics. The customer who is a single, middle-aged individual with a high or average education level and income and comes from a large city will tend to spend more. In addition, the model allows the assessment of the impact of various demographic factors (such as age, marital status, monthly income, education level, residential location, occupation) on the increase or decrease of such consumer spending (that is, an additional advantage of the model). Model 2 estimates lengths of stay in the theme park. For example, married people from small towns tend to remain longer than a single person from a large city. As in the previous model, the model here allows a simulation of the impact of individual demographic characteristics on the length of stay in E-Da World. As a result, managers can evaluate not only what segment of the customer base offers them the greatest economic advantage but also how specific demographic factors influence the behaviour of customers. Accordingly, the two models presented herein are powerful tools for managing this type of business.

There are criticisms regarding fuzzy logic, however, with respect to what it is and what it has to offer. Zadeh (2008) states, "fuzzy logic is a precise logic of imprecision and approximate reasoning and that's why fuzzy logic is needed to deal effectively with fuzzy reality since it is much more than a logical system". Wessely (2011) argues that fuzzy logic is a great tool to serve as a model of reality, particularly in human-centric fields such as economics, law, linguistics and psychology. It is precisely for this reason that the results of this study will provide reliable forecasting information related to visitor expenditure for theme park management. Collecting information is important process (Ku, 2013) and as a result, theme park managers will be able to make more precise estimations regarding which customer segments are more profitable for their theme park. Moreover, it will be easier for marketing departments to calculate on which focus groups they should concentrate, and human resource and logistics departments will be better equipped to efficiently and effectively to allocate their resources. The success of this study provides useful guidelines for improved managerial decisions for other operators in the tourism industry as it can serve as a starting point for examining diminishing uncertainties. Further, understanding of the economic and temporal behaviours of theme park visitors can enhance the management of attractions and contribute to growth in tourist expenditures.

This paper is organised into five sections. Section one is the introduction. Section two presents an overview of the literature on theme park management and fuzzy logic concept, the research methodology is discussed in section three, and section four proposes forecasting models for customer expenditure and length of stay in the E-Da World. The last section offers a number of general conclusions as well as some specific recommendations.

2. Literature review

2.1 Theme Park Management

During the past decade, theme and amusement parks have given a strong boost to the hospitality/tourism industry worldwide (Formica & Olsen, 1998). North America represents the largest segment of this leisure industry with approximately 600 amusement and theme parks (Geissler & Rucks, 2011) while Asia represents the fastest growing region of the global theme park industry as the top 20 theme parks have registered 103.3 million visitors and a spectacular growth of 7.5% for the year 2011 (IAPPA, 2012). In addition to this bumper performance, four (4) out of the top ten (10) of the most visited theme parks in the world are located in Asia (Cheng, Guo, & Ling, 2013).

Given the harsh level of competition among operators, theme park managers are currently engaging in a battle to attract more visitors (Tsai & Chung, 2012) as they are having to contend with other aggressive competitors such as holiday parks, scenic tourist locations, leisure resorts and museums in a variety of exotic tourism destinations (Lewis & Booms, 1983). Competitors are no longer just local sites as visitors can easily travel from one country to another for the enjoyment of a range of leisure services (Wagenheim & Anderson, 2008).

As a result of the rapidly changing competitive environment in which they operate, overseeing the general operations of theme parks and monitoring visitor satisfaction are crucial for theme park managers as their success and survival depends on attendance. Yalowitz and Bronnenkant (2009) suggested that theme parks can improve their resource allocation by allocating their staff to high demand activities with the aim to more effectively serve visitors during periods of peak demand. Managers should also consider using different strategies to encourage visitors to stay longer at profit-making places, while at the same time, they should identify those activities that are least appealing to visitors and, hence, constitute poor profit earners (Tsai & Chung, 2012). Nonetheless, given that overall customer strategy is important, any theme park may be subject to failure due to inappropriate external marketing strategies or the incorrect scheduling of internal operations (Dzeng & Lee, 2007), which may be the result of attracting low-profitability customers in the first place. Visitation flow is higher in the morning and during peak seasons (Alexander, MacLaren, O'Gorman, & White, 2012; Vassiliadis, Priporas, & Andronikidis, 2013), Previous empirical research further more found that visitors generally visit theme parks on weekends or long holidays (Tsai & Chung, 2012; Yalowitz & Bronnenkart, 2009).

According to Tsai and Chung (2012), if a theme park manager thoroughly understand his visitors' behaviours, that is, he knows which rides have generated the greatest profits, which shows have brought in the greatest number of visitors and which shops and squares have attracted the greatest attention, then he can significantly improve consumer satisfaction levels. The Disney corporation invested 1 billion USD on technology to track theme park visitors to better determine where more staff is needed, which foods and restaurants are most popular, and what types of souvenirs are most preferred by the customers (Palmeri, 2014)

Cheng et al. (2013) found that pricing and value for money were perceived by visitors, as well as by theme park operators, as the major criteria for evaluating the attributes of a theme park. As profitability of a theme park's operations depends on how managers perceive and are able to influence visitor behaviour on site, analysing visitor behaviour is critical to profit generation as it provides insights into influencing visitors to spend their money in ways that are advantageous to the park (Geissler & Rucks, 2011). As this is often related to time spent, park planners and managers should obtain fundamental information on the way visitors spend their time by using appropriate temporal scales (Birenboim, Anton-Clavé, Russo, & Shoval, 2013).

2.2. Fuzzy logic concepts

There is little extant research that combines theme park management and fuzzy logic. One study is that of Lee and Huang (2009), who investigate the difference between the traditional Kano model and its combination with fuzzy theory. Although their investigation is a good starting point on using fuzzy logic in theme park management, their study did not strictly relate to forecasting. Rather, they proved that a fuzzy Kano model helps respondents express the correct extent of their feelings in questionnaire items by using simple category membership that avoids the use of scaled metrics, arguing that such metrics do not effectively represent the vagueness in the degree of personal opinion that a respondent may possess. Another study is that of Cheng et al. (2013), who examined theme park visitor satisfaction in Taiwan (R.O.C.) using a fuzzy importance-performance analysis. They found that while amusement consumption (entrance ticket, food, and beverage price) are among the most important aspects for visitors, these factors were met by inadequate performance highlighted by low levels of consumer satisfaction. In addition, their research provided important insights into theme park performance. For example, they suggested that theme park managers must be exceptionally conscientious with respect to food prices, sanitary food preparation, beverage services, and convenient dining and that they maintain reasonable park entrance fees. Although these two studies employed, to some degree, fuzzy theory as a management tool for theme parks they did not investigate how fuzzy theory can create a forecasting model. Accordingly, it is this gap that is addressed by this paper as it advances a fuzzy logic model for predicting customer expenditure and length of stay.

The majority of the systems functioning nowadays, in all the areas, must have decision capabilities e.g. finance, medicine, engineering, etc. (the issue of evaluation of classification algorithms in such systems is discussed in the literature – e.g.: Kou, Lu, Peng & Shi, 2012; Kou, Peng & Wang, 2014). They have to be able to provide an answer to a considered question.

Some of them are using classical (conventional) logic, which will always provide affirmative or non-affirmative answers, meaning “white” or “black”, “no” or “yes”, “long” or “short” (Korol & Korodi, 2011). These sets of answers are considered to be the set of two truth-values {0,1}. In many cases the “0” or “1” type of answers are not presenting enough relevance. The reason is that many questions cannot be answered correctly only through two fix values. Many phenomena in management are fuzzy, and they are treated if they were crisp. Moreover, very often the input variables and data of forecasting models cannot be determined in the precise sense. Therefore, the fuzzy logic provides an appropriate tool in modeling the imprecise models. The concept of fuzzy logic was introduced by Zadeh in 1965. Fuzzy set theory permits the gradual assessment of the membership of elements in relation to a set. The fuzzy set “A” in a non-empty space X ($A \subseteq X$) can be defined as (Zadeh, 1965):

$$A = \{(x, \mu_A(x)) | \, x \in X \} \tag{1}$$

where $\mu_A : X \rightarrow [0,1]$ is a function for each element of X that determines the extent to which it belongs to set A. This function is called a membership function of fuzzy set A.

In the fuzzy set theory an element may partially belong to a certain set, and this membership may be expressed by means of a real number in the interval [0,1]. Larger values denote higher degrees of set membership. Thus, the membership function $\mu_A(x) : U \Rightarrow [0,1]$ is defined as follows (Syau, Hsieh & Lee, 2001):

$$\forall_{x \in U} \mu_A(x) = \begin{cases} f(x), x \in X \\ 0, x \notin X \end{cases} \tag{2}$$

where: $\mu_A(x)$ –function defining membership of element x to set A, which is a subset of U; f(x) - function receiving values from the interval [0,1]. The values of this function are called the degrees of membership.

A fuzzy logic model is constructed by a set of “IF-THEN” rules to describe the relationship among the input and output variables. An important distinguishing feature between fuzzy logic and the traditional expert system is that the rules in fuzzy logic can be described through the use of linquistic variables instead of the numerical variables (Yanhui, Deyu & Kaishe, 2013). Furthermore, in the fuzzy logic model there is a mechanism for describing the degree of membership of an element to the set and the use of several terms to classify the linguistic variables. For example, a fuzzy logic rule can be stated as follows:

IF *customer's income* is <u>low</u> AND *customer's age* is <u>old</u> AND *country's GDP growth* is <u>low</u>

THEN *probability of spending in theme park* is <u>small</u>

where *customer's income, customer's age, country's GDP growth* and *probability of spending in theme park* are linguistic variables, and <u>old</u>, <u>low</u>, <u>small</u> are their terms.

With the membership function, all economic phenomena that contain a certain part of the lack of precision can be better described and used in the economic model. For example, the following statements are imprecise:

- the customer is old/young/middle age,
- the customer's income is low/average/high,
- the unemployment rate should decrease/increase next year.

Imprecision of these statements is the inability to accurately determine the values of all variables occurring in it. When using bivalent logic an economist is forced to make a decision based on imprecise - fuzzy information, ie whether the customer is going to spend "more" or "less". In the case of the application of fuzzy sets an analyst uses a smooth transition between the total membership [uA (x) = 1] and total non-membership [uA (x) = 0] of the analyzed phenomenon.

3. Research Approach

The background to the case

Located near Kaohsiung City in Southern Taiwan, E-Da World is a newly established entertainment and shopping district built in 2009 by the E-United Group, a conglomerate that is rated as the fifth largest steel manufacturer worldwide. It consists of a theme park, a shopping mall (E-Da mall), and two hotels (Skylark and Crowne Plaza). Its design, based on the theme of ancient Greek mythology, serves as its positioning and differentiation strategy. The E-Da Theme Park, designed as a Greek island, includes a replica of Santorini, the Aegean Sea Village, and the Trojan Castle, which is based on Homer's famous stories of Troy. The 47 entertainment facilities in the theme park attract thousands of visitors annually. The adjoining E-Da mall covers 190,000 square meters and consists of outlets for 300 worldwide brands. It also houses an 85-metre Ferris wheel, the largest in Southern Taiwan.

To collect data for the study, a pencil-paper based questionnaire was used. The questionnaire was designed to collect data related to demographic characteristics of the visitors, their visitation experiences and their level of satisfaction with the services provided by the theme park industry in general and their perceptions of the service quality in the E-Da Theme Park in particular. To examine their visitation experiences and their level of satisfaction, an importance-performance analysis and a time–cost instrument were implemented. Using random sampling, 689 visitors completed the questionnaire during the months of December 2012 and January 2013, the peak months for the theme park. Of the 689 surveys, 546 of the responses were appropriate for statistical analysis.

Content validity analysis

The content validity was based on a literature review and a panel of tourism experts. The questionnaire was reviewed by five (5) experts in theme park management, all who reported that the questionnaire was suitable as a measurement tool for the analysis of visitor behaviour. The use of the time block instrument to record activities and expenditures was also deemed appropriate.

Demographics

Based on demographic characteristics 35.5% of the sampled visitors were male and 64.5% were female. Of those sampled, 39.7% were students, 2.8% were housekeepers, 0.7% were farmers, 3.5% were unskilled or unemployed individuals, 33.3% were employees in the private sector, 5.0% were public clerks, 6.3% were executives and 3.9% were independent professionals. In addition, 0.7% of the visitors were retired and 4.1% were unspecified. With respect to age, 3.5% of the visitors were between the ages of 15 and 17 years, 38.2% were between the ages of 18 and 22 years, 29.2% were between the ages of 23 and 30 years, and 21.4% were between the ages of 31 and 40 years. Of the remaining respondents, 5.8% were between 41 and 50 years of age, and 1.9% were between 51 and 60 years of age. With respect to marital status, 73.6% of the sampled visitors were single, 23.6% were married, 2.2% were divorced and 0.6% were widowed. The educational levels of the respondents of this sampled, 3.2% had a primary level of education, 18.0% had a secondary level of education, 69.9% reported a tertiary level of education, and 8.9% had attained postgraduate level. The respondents surveyed were residents of the largest cities of Taiwan. The profile per city was Kaohsiung (33.3%), Tainan (10.9%), Taipei (20.6%), Chiayi (5.7%), non-specified cities (29.5%).

The results of the study further revealed that 47.1% of the visitors spent between 100 and 300 $NTD on cafeterias in the E-Da World Theme Park, 29.9% spent less than 100 $NTD and a few spent more than 300 $NTD. The expenditure per visitor on food/drink in the theme park varied from 100 to 500 $NTD. However, 4.2% of the visitors spent less than 100 $NTD on food/drink, while the majority (61.5%) of the visitors spent more than 300 $NTD. With respect to expenditures for tickets, only 2.4% spent less than 100 $NTD, while 36% of the visitors spent between 100 and 300 $NTD. Based on additional results, the average expenditures for travel, food etc. per visitor prior to arriving at the theme park were between 100 and 500 $NTD. The results also indicate that the average expenditures on activities within the theme park fall into the same bracket, excluding the entry ticket price. After visiting the theme park, 15.4% of the visitors expected to spend over 900 $NTD and 26.4% expected to spend less than 300 $NTD on food and purchases at the park's retail outlets.

The justification of the used methodology

Fuzzy logic has been widely used in machinery, robotics and industrial engineering. It has recently found extensive applications in a variety of industrial systems, consumer products (Azagedan, Porobic, Ghazinoory, Samouei & Kheirkah, 2011), and also in areas of management – eg. quality management (Homayoni, Hong & Ismail, 2009), inventory management (Chen & Chang, 2008), planning production capacity (Sudiarso & Labib, 2002) and human resources (Canós, Casasús, Liern & Pérez, 2014; Canós 2013; Fúller, Canós & Canós, 2012; Canós & Liern, 2008).

The advantages of fuzzy rule-based classifier are as follow:

- it produces models that can be interpreted easily,
- the models are relatively easy to create,
- they can be modified to handle data containing missing attribute values,
- the performance of fuzzy sets models are proved to be highly effective in variety of fields (medicine, engineering, finance etc.),
- speed and ease of update to the changing conditions. In case of statistical models and artificial intelligence models the desire to change the slightest model parameter involves the necessity of estimation of a whole new model form.

4. Fuzzy logic forecasting models

4.1. The structure of the models

The objective of this research was to create two fuzzy logic models – one to forecast the average level of customer spending in the E-Da World Theme Park, and the other to predict the average length of customer stay. Customer expenditure is denominated in new Taiwanese dollars ($NTD) and the length of stay is given in number of days.

Six demographic variables were selected for creating the two fuzzy logic models: age of customer, marital status, monthly income, education level, residential location, occupation.

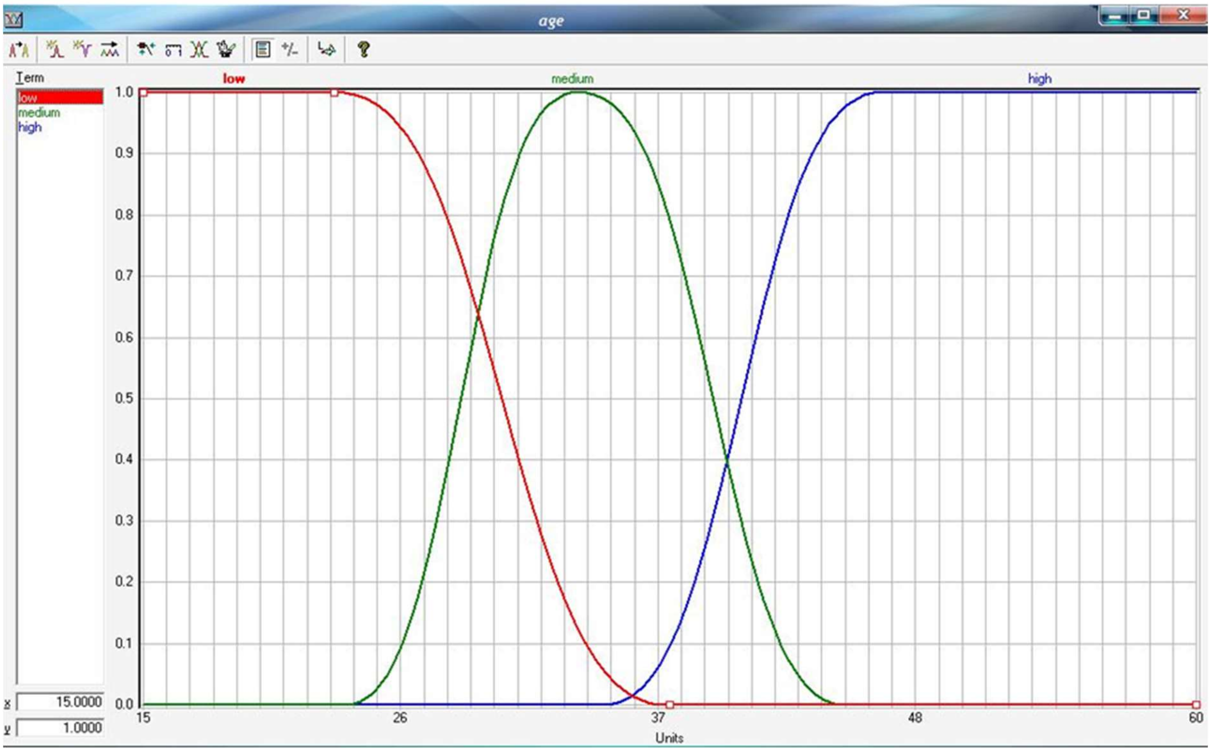
For each entry variable for both models (where the level of these variables are fuzzy values), the authors identified the fuzzy sets (the subsets of a set of values of the entry variable) and their corresponding membership functions. The fuzzy sets and the thresholds for all membership functions are presented in Table 1. The fuzzy sets and the shape of membership functions are based on extensive prior research conducted in a number of economic areas designated by the authors.

Table 1. Entry variables and their membership functions

Variable	Description of membership functions and their range of values
Customer's age	"Low" – less than 37 "Medium" – from 24 to 45 "High" – more than 36
Marital status	"Divorced or widow" – less than 1.25 "Married" – from 0.6 to 1.7 "Single" – more than 1.25
Monthly income	"Low" – less than 34,000 NTD "Average" – from 22,000 NTD to 46,000 NTD "High" – from 34,000 NTD to 58,000 NTD "Very high" – more than 46,000 NTD
Education level	"Low" – less than 1.5 "Medium" – from 0.8 to 2.2 "High" – more than 1.5
Residential location	"Small" – less than 0.65 "Large" – more than 0.35
Occupation	"Low" – less than 1.5 "Medium" – from 0.8 to 2.2 "High" – more than 1.5

Figure 1 presents an example of how the fuzzy sets were defined, using membership functions as the first demographic variable – age. There are three membership functions: "low", "medium" and "high". All values less than 23 are young customers and thus belong to the fuzzy subset "low" and are assigned a degree of membership equal to 1. The subsets "medium" and "high" are assigned a degree of membership equal to 0. All values greater than 46 belong to the fuzzy subset "high" and are assigned a degree of membership equal to 1 (customers older than 46 years are classified as "high"). Values in the range from 24 to 46 belong to two fuzzy subsets ("low and medium" or "medium and high") with different values of membership functions.

Figure 1. Example of fuzzy sets for variable "Age" with membership functions



The output of the first fuzzy logic model is a variable representing the forecast of the average amount of customer spending per combination of all activities (cafes, restaurants, tickets, mall stores, etc.). This variable has a value that ranges from 0 $NTD to 1,000 $NTD (Figure 2). There are four membership functions that define the output variable (Figure 2): "small", which represents a low level of spending; "medium-small", which defines less than average spending; "medium-large", which indicates higher than average spending; and "large", which represents the highest level of spending.

In the case of the second fuzzy logic model, three membership functions are available for the output variable forecasting the length of stay for the customer visiting the theme park

(Figure 3): "short", which represents a 0-1 day stay; "average", which indicates a 2-3 day stay; and "long", which denotes stays in excess of 3 days.

Figure 2. Defined membership functions for output variable of the first model

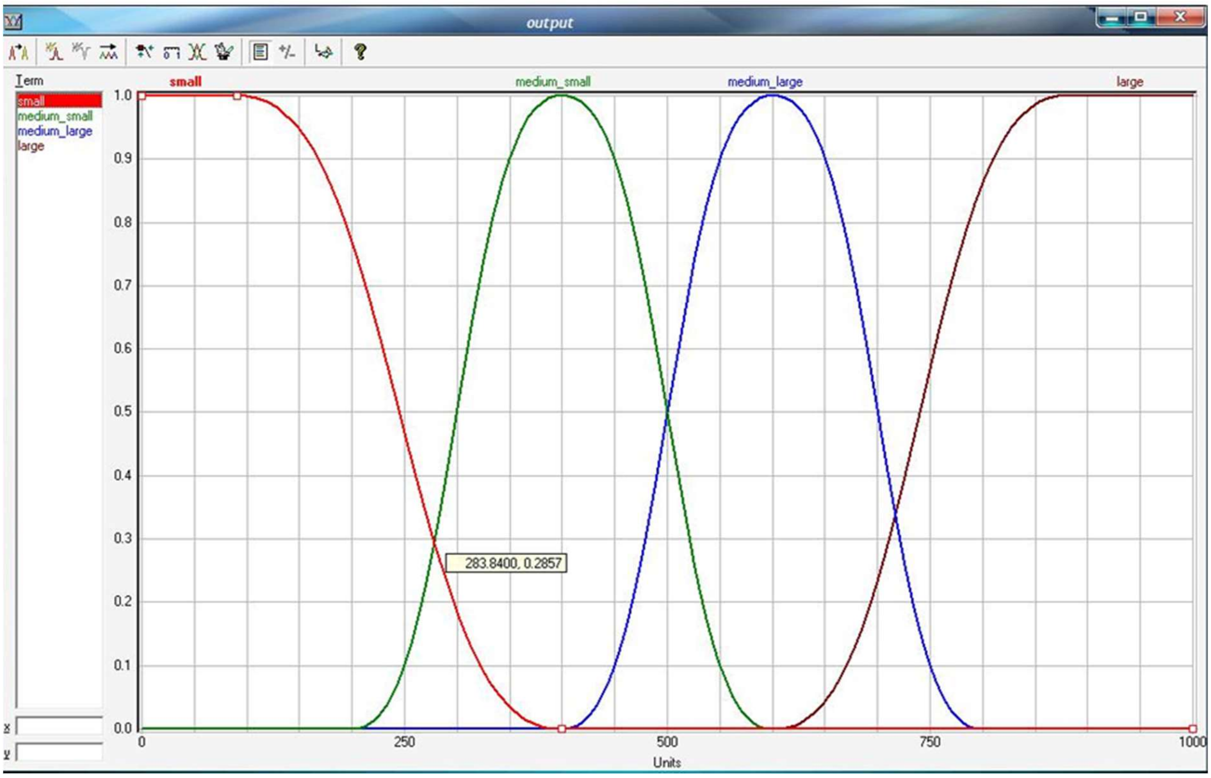
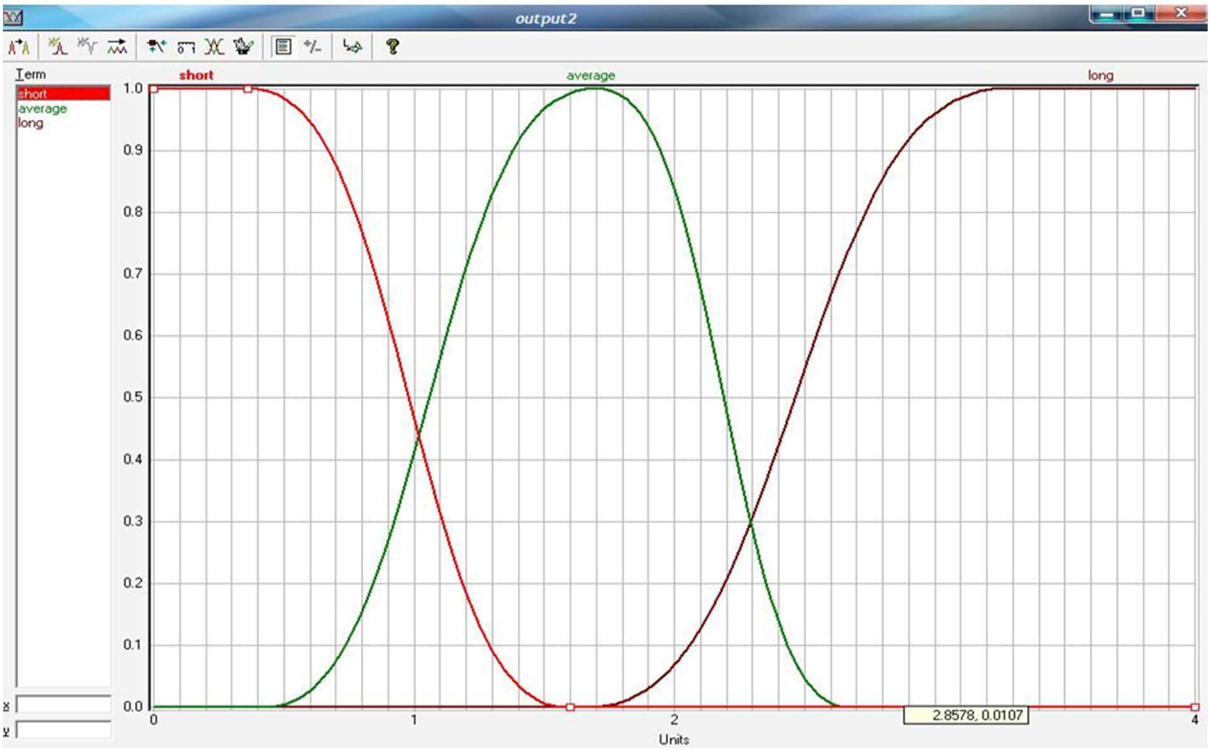


Figure 3. Defined membership functions for output variable of the second model

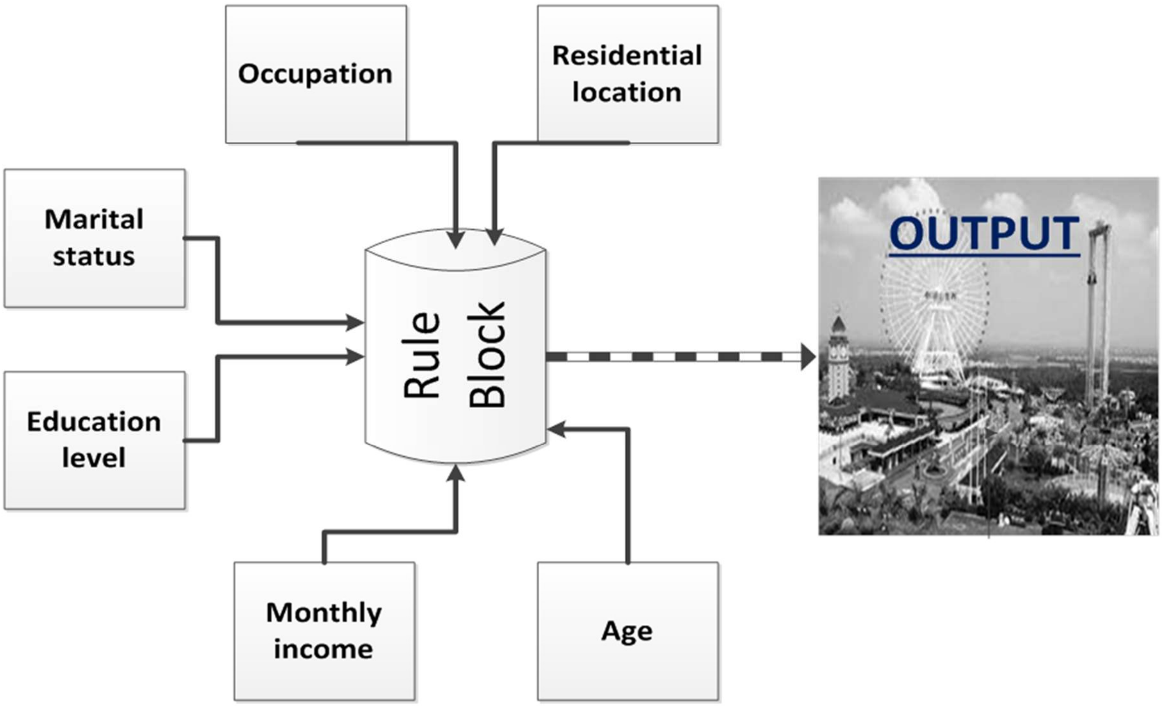


4.2. The Fuzzy Logic Models

The models are based on sets of decision rules written by the authors in the form of IF-THEN statements where expert knowledge of the research model is stored (Magni, Malagoli, & Mastroleo, 2006). Using prior research studies and in-depth experience with similar fuzzy logic models, the development of a new fuzzy model does not necessarily require an in-sample data set. These two models have been developed with the expert knowledge of the authors that they have accumulated from over ten years of experience in developing fuzzy logic models for economics and forecasting.

The schematics of the developed fuzzy logic models are shown in Figure 4. While the structure is the same for both models, the decision rules are different. In this diagram, there is one rule block, six entry variables and one output variable.

Figure 4. Diagram of fuzzy logic model for forecasting customer expenditure and length of stay at theme parks.



The complete set of decisions includes 648 rules for each model, though different specific rules apply in each case. Due to the large size of these two rule sets, a selection of 20 exemplary decision rules are described for the expenditure model (Tabel 2) and 10 for the second model (Table 3)[1].

Table 2. The set of decision rules for the fuzzy logic model forecasting customer expenditures

Rule Block -- 'Expenditure'							
No.	**IF "age" is:**	**IF "education" is:**	**IF "income" is:**	**IF "occupation" is:**	**IF "residence" is:**	**IF "status" is:**	**THEN "output" is:**
1.	low	low	low	low	small	divorced widow	small
2.	low	low	low	high	small	divorced widow	small
3.	low	low	low	high	small	married	small
4.	low	low	low	medium	small	single	small
5.	low	low	average	high	small	divorced widow	medium_small
6.	low	low	average	medium	large	single	medium_smal

[1] A full set of the decision rules is available from the authors for all researchers or interested readers.

							l
7.	low	low	average	low	large	Single	medium_small
8.	low	low	low	high	large	single	medium_small
9.	low	low	average	Medium	Small	divorced widow	medium_small
10.	high	high	high	low	small	single	medium_large
11.	high	high	very high	medium	small	married	medium_large
12.	high	high	high	medium	large	Married	medium_large
13.	high	high	very high	low	small	Single	medium_large
14.	high	high	very high	high	small	Divorced widow	medium_large
15.	high	high	high	low	small	Married	medium_large
16.	high	high	very high	low	large	Married	large
17.	high	high	very high	medium	large	Single	large
18.	high	high	very high	high	small	Married	large
19.	high	high	very high	medium	large	Married	large
20.	high	high	very high	high	large	Married	large

Table 3. The set of decision rules for the fuzzy logic model forecasting the length of stay of customers at theme park

Rule Block "Length of stay"							
No.	**IF "age" is:**	**IF "education" is:**	**IF "Income" is:**	**IF "occupation" is:**	**IF "residence" is:**	**IF "status" is:**	**THEN "output2" is:**
1	Medium	Low	Low	Low	Large	Single	Short
2	Medium	Low	High	Low	Small	Married	Average
3	Medium	Medium	Very high	Medium	Small	Married	Long
4	High	Low	Low	Medium	Small	Single	Average
5	High	Low	Low	Low	Large	Single	Short
6	High	Low	High	High	Small	Divorce Widow	Long
7	Low	High	Very high	High	Small	Married	Long
8	Low	High	Average	High	Large	Married	Average
9	Low	Average	High	Low	Large	Single	Short
10	Medium	High	Average	Low	Large	Married	Average

4.3. The effectiveness of the models' forecasts

Of the 546 surveys answered by a random selection of customers visiting the E-Da World Theme Park, 500 were chosen to test the effectiveness of the models. The authors calculated the average expenditure of customers on activities, including cafes, restaurants, tickets, shopping malls, and others (question numbers V64, V65, V66, V67 and V69 of the survey – Appendix 1). There are six possible ranges of expenditures (in $NTD): less than 100; 101-300; 301-500; 501-700; 701-900; more than 900. With respect to the length of stay for customers visiting the E-Da World Theme Park, there are the following possible responses (in days): 0 (means hourly stay less than one full day), 1 day, 2 days, 3 days, more than 3 days.

The tests of the fuzzy logic models showed that Model 1, forecasting the average level of customer spending, performed best with an 86% level of effectiveness. In other words, the forecasts for 430 out of 500 customers were in the actual range of expenditures as stated by the individual respondents. The forecasting effectiveness of Model 2, length of stay, was 82%, which is also an exceptionally good performance.

In the case of forecasting the level of expenditures, there is an important question regarding the type and the size of errors generated in Model 1. The type of error is defined to mean whether the forecasted level of spending is in a class below (underestimation) or in a class above (overestimation) the class recorded for the actual customer's expenditure. Based on the total number of errors, 76% of the generated errors were overestimations, while only 24% were underestimations. This means that for 53 of the 70 customers whose forecasts were incorrect, the model forecasted higher expenditures than those actually reported, thus accounting for 10.6 percentage points of the total error rate of 14%. Of the remainder 17 customers, the forecasted results were underestimated, thus accounting for 3.4 percentage points of the total error.

Although the occurrence of errors in the fuzzy logic models is a useful efficiency measure, another important question regards the size of the errors. The size of the errors is the number of class ranges that the model forecasts that are over or under the actual class the survey data from the respondents had provided. For example, if the customer spent 200 $NTD (3rd class of expenditures) while the model forecasts the expenditure at the level of 600 $NTD (5th class of expenditures), it is classified as an overestimated error by a count of 2 classes. In both situations (underestimation and overestimation of errors) most errors are only by a count of 1 class. In case of overestimation, only 7.5% of the errors are higher than 1 class and 92.4% are in the range of ±1 class error. In case of underestimation, 23.5% are higher than 1 class, while 76.5% are in the range of ±1 class error.

Summarising the effectiveness of the fuzzy logic models applied herein, it can be said that the results are extremely good and certainly promising with respect to the future use of this technique in theme park forecasting management and tourism management in general due to:

- the high predictive effectiveness of both models (Model 1 - 86% and Model 2 - 82%);
- the low degree of error, e.g., Model 1 the 14% erroneously forecasted expenditures are mostly minor errors – usually with a bias to over-estimate, although predominantly only 1 class in size;
- the high practical values of the models (the conclusions can be applied in other tourism management areas);
- the ability to explain how to solve management problems as the transparency of the fuzzy logic model makes the decision rules clear to see and analyse (in contrast to models based on artificial neural networks that operate on the black box principle).

5. Conclusions

Developed many decades ago, fuzzy logic theory is now being implemented in several industries and is proving to be a highly successful tool. However, despite its use in numerous industrial settings, it has not yet been widely applied in the tourism industry. This paper develops a novel approach for forecasting customer expenditure and length of stay at tourist venues using fuzzy logic methodology. The analysis presented herein demonstrates that fuzzy logic can be an accurate, useful and powerful tool in tourism management analysis, as the programmed models can be easily used by managers as a decision aid and strategy evaluation tool in the process of forecasting theme park revenues. For future development directions with respect to theme park management, the authors recommend detailed research into other factors that influence the behaviour of the customer. Such factors include psychological, economic, geographical, social, and cultural dimensions.

The lack of forecasting accuracy by traditional models (e.g., logit or probit) may lead to major consequences for theme park viability, as such models operate in an intensely competitive financial environment. The two innovative models evaluated here are of high practical value for theme park survival as high levels of predictive efficiency characterise the models.

This research is methodically and analytically innovative from two perspectives. First, we use a new approach (fuzzy logic) in theme park management where data collected is limited, and high quality information is difficult to obtain. Second, we demonstrate ways to significantly improve forecasting tactics in tourism management with transparent models of inputs and outcomes. It is useful to note that such models can be used in many other aspects of tourism, such as hotel management, amusement parks, national parks, cruises, snow skiing and MICE events, where revenue per visitor is a prime consideration.

The authors hope that this research will add value to the existing literature about theme park management and will initiate a discussion about other possibilities for the implementation of fuzzy logic theory and modelling in the tourism industry. Due to its wide applicability and easy of use and adaptations, this paper offers the reader not only a particular form of two models forecasting customer expenditure and length of stay, which can be used in practice, but also an entire tool which can be updated and adopted for own needs.

Future research is recommended as this study could be repeated during non-peak months as the results might be different between pick and non-peak months. More of that since in Taiwan there are more than 15 theme parks it will be interesting all of them to be examine at national level since client's expectations may change in the theme park offer. Differences in client's characteristics could be used to improve the offer as well as to customize the marketing strategy to a selected group of visitors.

References

Alexander, M., MacLaren, A., O'Gorman, K., & White, C. (2012). Priority queues: Where social justice and equity collide. Tourism Management, 33, 875-884.

Azadegan, A., Porobic, L., Ghazinoory, S., Samouei, P., & Kheirkhah, A. (2011). Fuzzy logic in manufacturing - a review of literature and a specialized application. International Journal of Production Economics, 132, 258-270.

Aziz, M., & Dar, H. (2001). Predicting corporate bankruptcy - where we stand? Corporate Governance Journal, 6(1), 18-33.

Birenboim, A., Anton-Clavé, S., Russo, A. P., & Shoval, N. (2013). Temporal Activity Patterns of Theme Park Visitors. Tourism Geographies, 1-19. doi:10.1080/14616688.2012.762540

Canós Darós, L. (2013). An algorithm to identify the most motivated employees. Management Decision, 51(4), 813-823. doi:10.1108/00251741311326581

Canós Darós, L., & Liern Carrión, V. (2008). Soft computing-based aggregation methods for human resource management. European Journal of Operational Research, 189(3), 669-681. doi:10.1016/j.ejor.2006.01.054

Canós Darós, L., Casasús Estellés, T., Liern Carrión, V., & Pérez Cantó, J. C. (2014). Soft computing methods for personnel selection based on the valuation of competences. International Journal of Intelligent Systems, 29, 1079-1099. doi:10.1002/int.21684

Chang, C., Shu, S., & King, B. (2014). Novelty in Theme Park Physical Surroundings: An Application of the Stimulus–Organism–Response Paradigm. Asia Pacific Journal of Tourism Research, 19(6), 680-699. doi:10.1080/10941665.2013.779589

Chen, S., & Chang, S. (2008). Optimization of fuzzy production inventory model with unrepairable defective products. International Journal of Production Economics, 113, 887-894.

Cheng, Q., Guo, J., & Ling, S. (2013). Fuzzy importance-performance analysis of visitor satisfaction for theme park: the case of Fantawild Adventure in Taiwan, China. Current Issues in Tourism, 1-18. doi:10.1080/13683500.2013.777399

Chiang, W., Chen, J., & Xu, X. (2007). An overview of research on revenue management: current issues and future research. International Journal of Revenue Management, 1(1), 97-128.

Dzeng, R.-J., & Lee, H.-Y. (2007). Activity and value orientated decision support for the development planning of a theme park. Expert Systems with Applications, 33(4), 923-935. doi:10.1016/j.eswa.2006.08.002

Formica, S., & Olsen, M. (1998). Trends in the amusement park industry. International Journal of Contemporary Hospitality Management, 10(7), 297-308. doi:10.1108/09596119810240933

Fúller, R., Canós Darós, L., & Canós Darós, M. J. (2012). Transparent fuzzy logic based methods for some human resources problems. Revista electrónica de comunicaciones y trabajos de ASEPUMA, 13(1), 27-41.

Geissler, G. L., & Rucks, C. T. (2011). The critical influence of customer food perceptions on overall theme park evaluations. Journal of Management and Marketing Research, 8, 1-15.

Heo, C. Y., & Lee, S. (2009). Application of revenue management practices to the theme park industry. International Journal of Hospitality Management, 28(3), 446-453. doi:10.1016/j.ijhm.2009.02.001

Homayoni, S., Hong, T., & Ismail, N. (2009). Development of genetic fuzzy logic controllers for complex production systems. Computers & Industrial Engineering, 54 (3), 1247-1257.

IAPPA. (2012). Amusement Park and Attractions Industry Statistics. Retrieved 05/08/2013, from IAAPA http://www.iaapa.org/resources/by-park-type/amusement-parks-and-attractions/industry-statistics

Joo, H. H., Kang, H.-G., & Moon, J. J. (2012). The Effect of Rain on the Decision to Visit a Theme Park. Asia Pacific Journal of Tourism Research. doi:10.1080/10941665.2012.724020

Korol, T. (2012). Fuzzy Logic in Financial Management In E. P. Dadios (Ed.), Fuzzy Logic - Emerging Technologies and Applications (pp. 259-286). Rijeka: InTech.

Korol, T., & Korodi, A. (2011). An evaluation of effectiveness of fuzzy logic model in predicting the business bankruptcy. Romanian Journal of Economic Forecasting, 3, 92-107.

Kou, G., Lu, Y., Peng, Y. I., & Shi, Y. (2012). Evaluation of Classification Algorithms Using MCDM and Rank Correlation. International Journal of Information Technology & Decision Making, 11(01), 197-225. doi:10.1142/S0219622012500095

Kou, G., Peng, Y., & Wang, G. (2014). Evaluation of clustering algorithms for financial risk analysis using MCDM methods. Information Sciences, 275, 1-12. doi:10.1016/j.ins.2014.02.137

Ku, E. C. S. (2013). Functional integration and systems implementation of customer relationship management in hotel industry: A multilevel analysis. International Journal of Information Technology & Decision Making, 13(01), 175-196. doi:10.1142/S0219622014500084

Lee, W. S., Graefe, A. R., & Hwang, D. (2013). Willingness to Pay for an Ecological Park Experience. Asia Pacific Journal of Tourism Research, 18(3), 288-302. doi:10.1080/10941665.2011.652970

Lee, Y.-C., & Huang, S.-Y. (2009). A new fuzzy concept approach for Kano's model. Expert Systems with Applications, 36(3), 4479-4484. doi:10.1016/j.eswa.2008.05.034

Lewis, R., & Booms, B. (1983). The marketing aspects of service quality. Chicago: American Marketing Association.

Ma, J., Gao, J., Scott, N., & Ding, P. (2013). Customer delight from theme park experiences. Annals of Tourism Research, 42, 359-381. doi:10.1016/j.annals.2013.02.018

Magni, C. A., Malagoli, S., & Mastroleo, G. (2006). An Alternative Approach to Firms' Evaluation: Expert Systems and Fuzzy Logic. International Journal of Information Technology & Decision Making, 05(01), 195-225. doi:10.1142/S0219622006001812

Milman, A. (2010). The future of the theme park and attraction industry: A management perspective. Journal of Travel Research, 40(2), 139-147. . doi:10.1177/004728750104000204

Palmeri, C. (2014). Disney bets big on visitor-tracking technology. Retrieved from http://www.businessweek.com/articles/2014-03-07/disney-bets-1-billion-on-technology-to-track-theme-park-visitors#r=most%20popular

Sudiarso, A., & Labib, A. (2002). A fuzzy logic approach to an integrated maintenance/production scheduling algorithm. International Journal of Production Research, 40 (13), 3121-3138.

Syau, Y., Hsieh, H., & Lee, E. (2001). Fuzzy numbers in the credit rating of enterprise financial condition. Review of Quantitative Finance and Accounting, 17, 351 – 360.

Tsai, C., & Chung, S. (2012). A personalized route recommendation service for theme parks using RFID information and tourist behavior. Decision Support Systems, 52(2), 514-527.

Tsang, N. K. F., Lee, L. Y. S., Wong, A., & Chong, R. (2012). THEMEQUAL—Adapting the SERVQUAL scale to theme park services: A case of Hong Kong Disneyland. Journal of Travel & Tourism Marketing, 29(6), 416–429. doi:10.1080/10548408.2012.691391

Tsaur, R.-C., & Kuo, T.-C. (2011). The adaptive fuzzy time series model with an application to Taiwan's tourism demand. Expert Systems with Applications, 38(8), 9164-9171. doi:10.1016/j.eswa.2011.01.059

Vassiliadis, C., Priporas, C., & Andronikidis, A. (2013). An analysis of visitor behaviour using time blocks: A study of ski destinations in Greece. Tourism Management, 34, 61-70.

Wagenheim, M., & Anderson, S. (2008). Theme park employee satisfaction and customer orientation. Managing Leisure, 13(3-4), 242-257.

Wang, C.-H. (2004). Predicting tourism demand using fuzzy time series and hybrid grey theory. Tourism Management, 25(3), 367-374. doi:10.1016/s0261-5177(03)00132-8

Wessely, P. (2011). Value Determination of Supply Chain Initiatives: Springer, Gabler.

Yalowitz, S., & Bronnenkart, K. (2009). Timing and Tracking: Unlocking Visitor Behavior. Visitor Studies, 12(1), 47-64.

Yanhui, Z., Deyu, L., & Kaishe, Q. (2013). Fuzzy decision implications. Knowledge-Based Systems, 37, 230-236.

Zadeh, L. (1965). Fuzzy sets. Information and Control, 8 (3), 38-353.

Zadeh, L. (2008). Is there a need for fuzzy logic? Information Science, 178, 2751-2779. doi:10.1016/j.ins.2008.02.012

Appendix 1

	Describe briefly the allocation of money during your visit in E-da Theme Park.	Less than 100NTD	100 300	301 500	501 700	701 900	More than 900 NTD	No Answer
1(V64)	At the café in the theme park I spent around							
2(V65)	At the restaurant in the theme park I spent around							
3(V66)	I spent for tickets for each person around							
4(V67)	Before I went to the theme park I spent at the mall around							
5(V68)	The morning before I arrive to the theme park I spent on average per person							
6(V69)	I spent money in other activities in the park around							