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Forecasting the Success of a New Service in Tourism by Computational Intelligence

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Abstract This paper deals with the development of six computational models that forecast the success of a new service in tourism industry. Conventional models like Adaptive Neuro-Fuzzy Inference System Neural Networks genetically involved, and non-conventional models like Discriminant, Logit, Probit and Weibull regression models are applied. Data that concern the criteria-variables of the success or failure of a new service in tourism are used as inputs to the models. In the case of the ANFIS model a special input selection technique is used. The forecasting accuracy of the ANFIS model is compared with the other proposed models using error type I and II, odds ratio. The results show that the ANFIS model, when applied to forecasting the success or failure of a new hotel service, achieves an overall classification percentage accuracy of 91.57%. Therefore, it may be a prudent way to capture uncertainty in relationships among input variables and output variables.

Keywords tourism services, tourism forecasting, service success forecasting, computational model, ANFIS

1. Introduction

Dynamic structure of the markets, increasing global competition and continued advances in technology mean that it is essential that companies produce more new products and services as both defensive and offensive tools. The importance of the service sector is ever increasing, so is the intensity of competition, Matters and Maruchek [1]. Service companies, like hotels, are forced to continuously innovate for survival in the increasingly competitive environment by introducing new services. The new services needed to maintain current service portfolio competitive, gain competitive advantage and extend customer base. Consequently there is a growing body of knowledge on new service development [2].

It is well known that the service designer is concerned with the systematic development and design of new services using various models, methods and tools, Bullinger *et al* [3]. Although service methods and tools are inexistence they are still considered to be in their infancy when compared to engineering methodologies for traditional product development can beused as well as for service development process [4].

Contrary to the extensive body of literature on concept evaluation and selection in new product development relative little attention has been paid to forecasting the success or failure of a new service. Indeed companies very often experience that the lunch a new services is problematical. Therefore the need of a model that can forecast if the lunch of a new service will be successful or fail is needed. To this end the forecasting model must address the following two basic questions. Firstly, what criteria-variables to employ as inputs to the model? Secondly, what method to use to build the forecasting model? From the methodology viewpoint, the work of Lin and Lee [5] is the earliest study to combine fuzzy theory with neural networks. In this work a hybrid model is used that combines the idea of a fuzzy logic controller, neural network structure and learning abilities into an integrated neural-network-based fuzzy logic control and decision system.

Chang et al [6] summarize those methods into five categories, these are: Fuzzy Adaptive Learning Control Systems (FALCON), Fuzzy back-propagation Network (FBPN), Rumelhart et al [7], adaptive neuro-fuzzy inference systems (ANFIS), Fuzzy Hyper Rectangular Composite Neural Networks (FHRCNNs), and fuzzy neural network (FuNN), respectively. Briefly, to build a neuro-fuzzy inference system, the applications of fuzzy neural networks in forecasting utilizes the results of trained neural networks to extract the crisp or fuzzy rules in order to build a neuro-fuzzy inference system. Furthermore it is known that soft computing forecasting tools such as fuzzy neural networks can solve certain problems with a better degree of accuracy and shorter computational times [8].

Although forecasting the success of new services has become an increasingly popular subject for practitioners and academics there has been little empirical work to investigate the most effective model. Therefore six computational models are compared and tested against each other for the purpose of forecasting the success of new services with the tourism sector. In this work the following computational models are used: ANFIS as proposed by Jang [9] to forecast new service success, Neural Networks genetically involved (NN), Discriminant, Logit, Probit and Weibull regression are compared and tested against each other. Here the ANFIS and NN models are considered as hybrid models. This work therefore extends and supplements the growing empirical literature on new services success by extending the neuro-fuzzy techniques to tourism services where a binary classification (0 = success, 1 = fail) is needed. It is worth noting that proposed computational models may be tuned and used in other services where a decision making process is required.

The approached used in this work is implemented using the fussy logic tool box that is embedded within MATLAB® (matrix laboratory) software. It is noted, however, that similar software, such as LabView may be used for this purpose: for example [10].

The paper is organized as follows. Section 2 provides review of existing methodologies to forecast the success of a service. The theoretical background of the proposed approaches is explained in section 3. The data preprocessing and input selection techniques are presented in section 4. Section 5 illustrates the proposed approach with a case study. Finally section 6 provides the conclusion and further research.

2. Literature Review

Edvardsson & Olsson [11] presented a Prerequisites Model that is the base for analyzing both large scale developing new services (NSD) and small scale changes on the service prerequisites decision. Later, Sungjoo Lee et al [12] presented a Decision Tree model to predict whether or not e-commerce would be successful for a variety of services. The suggested model has the largest percentage of predicting accuracy (70%-80%) compared to regression discriminant models. Menor and Roth [13] offered a two-stage approach for the development and validation of a new multi-item measurement scales reflecting a multidimensional construct called NSD competence. Smith et al [14], showed that a successful service design and NSD process can be achieved by combining a panoramic, or holistic, approach to NSD with a high level of precision at the micro level. Kitsios et al [15], estimated the criteria that contributes to the success of NSD in the hotel sector, followed by Ozer [16] who suggested that two new factors (task structuring and the expertise sharing) may be use in predicting the future success of online shopping and sport services. Jaw et al [17] conceptualized the impact of service characteristics, market orientation, and efforts in innovation to NSD performance where mixed methods of qualitative and quantitative research are used. Lee et al [18], focused on feasibility analysis at the concept development stage, to estimate new service concepts (NSCs) using a group of Analytic Hierarchy Process (AHP). Kim and Yoon [19] went on to present a new approach towards new service consent generation based on agent-based simulation (ABS). Applying the Activity Theory, Lin and Hsieh [20] estimated the dynamics of complex service innovation system and modelled the co-relationship between the entities in tele-health service projects. Homburg and Kuehnl [21], have provided a discourse on the interaction between internal and external integration practices to the success of new product and new services. Moser et al [22], present a genetic PSS development process where product and service development process is analyzed and compared to a PSS development process. Yang et al [23], support that frontline employees' creativity can increase NSD and that frontline employees' operational improvement competence (OIC) can enhance their creativity. Zhang et al [24], present a non-additive multiple criteria analysis method based on the λ_k fuzzy measure and the Choquet integral, suitable for the evaluation and the improvement of airline service quality performance. A new way in designing the appropriate methodology for Product Service System (PSS) problems is proposed by Tran and Park [25]. They present eight groups (holistic approach, practical approach, co-creative approach, systemic approach, life cycle approach, evaluable approach, computer aided approach and proved approach) with twenty-nine criteria for this reason. Konu [26], examined the importance of ethnographic approaches in NSD in tourism. A hybrid method for hotel recommendation has been proposed in which dimensionality reduction and prediction techniques, Nilashi et al [27]. They develop the multi-criteria CF recommended system for hotel recommendation and they try to improve the success of the forecasting by using Gaussian mixture model with Expectation Maximization (EM) algorithm and ANFIS. The suggested methods are applied and the results show that there is high percentage of accuracy as far as the hotel suggestion is concerned.

3. Theoretical Background

A brief theoretical background of the proposed computational models: Neural Networks genetically involved, ANFIS, Discriminant, Logit, Probit and Weibull regression model is given in this section.

3.1 Neural Network model

Artificial neural networks are often classified into two distinctive training types, supervised and unsupervised. Supervised training requires training pairs that are input vectors as well as corresponding target vectors. The process of back-propagation is a good example of the supervised training type and is the most popular training method in the Artificial Neural Networks (ANN) literature. The reason for the success of the Multilayer Perceptron (MLP) and its learning algorithm, BP, is that the outputs of the BP network are the estimates of posterior probabilities that have a central role in statistical pattern classification theory [28]. Neural networks do not require the a priori determination of a functional model form and have been theoretically shown to be universal approximators under certain conditions [29]. In traditional techniques the functional form is first determined followed by an estimate of its parameter. In the neural network approximation, both the function approximation and parameter estimation are done simultaneously. Thereby the evaluation of multiple models becomes an exercise to determine the appropriate number of parameters to satisfy the approximate underlying function. This is more difficult than in traditional methods because the resulting parameters do not have the natural interpretations that exist in model-based forecasting.

In a feed forward network the following adapted form can be used for a discrete binary choice model, predicting the probability p_i for a network with k^* input characteristics and j^* neurons:

$$n_{j,i} = \omega_{j,0} + \sum_{k=1}^{k^*} \omega_{j,k} x_{k,i} \quad (3.1.1) \qquad N_{j,i} = \frac{1}{1+e^{-n_{j,i}}} \quad (3.1.2)$$

$$p_i = \sum_{j=1}^{j^*} \gamma_j N_{j,i} \quad (3.1.3) \qquad \sum_{j=1}^{j^*} \gamma_j = 1, \gamma_j \geq 0 \quad (3.1.4)$$

The probability p_i is a weighted average of the log-sigmoide neurons $N_{j,i}$, which are bounded between 0 and 1. Since the final probability is also bounded, the final probability is a weighted average of these neurons.

This feed forward network comprises an input layer, an intermediate hidden layer which has three neurons, and an output layer. It is worth noting that one hidden layer commonly used in economic and financial applications [30]. The model has twenty inputs nodes that represent the service's characteristics and one output node that represents the binary classification. The neuron transfer function applied is a sigmoid function, which exhibits desirable properties such as being nonlinear and continuously differentiable. The neural network represents the way the human brain processes input sensory data, received as input neurons, into recognition as an output neuron. The neural network training is carried out using a genetic algorithm for the adjustment of the weights. After the network reaches a satisfactory level of performance, it learns the relationships between independent variables (service criteria) and dependent variable (success or fail). The pattern values provided for the input nodes are linearly mapped between 0 and 1.

3.1.1 Genetic algorithm for Neural network training

To train the neural network an optimization method is used based on genetic algorithms. Genetic Algorithms (GA) are a class of probabilistic search techniques based on biological evolution. In the 1960s Holland presented the first genetic algorithm to allow computers to solve difficult combinatorial problems, such as function optimization and machine learning [29]. The search strategy is based on a computationally simulated version of "survival of the fittest." In an attempt to find the optimal solution, the algorithm mimics the process of natural selection by testing the fitness of the individuals and determining if they will be selected to reproduce. Individuals in the population represent knowledge through a group of chromosomes, each defining a feature, or constraint, of the search space. The search process for potential solutions is conducted through repeated iterations both from within the population and its external environment, and converges to what is regarded as the fit solution [31].

The process of genetic evolution is initiated by randomly selecting a population, and evaluating each of its members. Once initialized, the following three biological operators are applied.

1. Selection: Individuals that constitute a population are assigned probabilities of survival based on their level of fitness.
2. Crossover: Is a process of "artificial mating" in which two individuals with high fitness values are combined so that their genes may produce an offspring with even better fitness. Crossover represents a way of moving through the space of possible solutions based on information gained from existing solutions. As an operator, crossover is described in terms of exploitation of information encoded in good individuals.
3. Mutation: Is the random adjustment of the individual's genetic structure. Mutation as an operator is described as the exploration of the search space.

It is noted that crossover requires two parents, and is implemented by taking some neurons from each parent to produce the child network. Whereas mutation requires only one parent and is conducted by a random modification of the neuron weights. In all three operators, the population size is set to 100 and the number of generation is set to 20.

3.2 Adaptive Neuro-Fuzzy Inference System

The design of the ANFIS model differs in form the NN model in that it is not fully connected, and not all the weights or nodal parameters are modifiable. Essentially, the fuzzy rule base is encoded in a parallel fashion so that all the rules are activated simultaneously to allow network training algorithms to be applied. As in Jang's original work, a back propagation algorithm is used to optimize the fuzzy sets of the premises in the ANFIS architecture, and a least squares procedure is applied to the linear coefficients in the consequent terms.

Let X be a space of objects and x be a generic element of X. A classical set $A \subseteq X$ is defined as a collection of elements or objects $x \in X$ such that each x can either belong or not belong to the set A. By defining a characteristic function for each element x in X, we can represent a classical set A by a set of ordered pairs $(x, 0)$ or $(x, 1)$ which indicates $x \in A$ or $x \notin A$, respectively. On the other hand, a fuzzy set expresses the degree to which an element belongs to a set. Hence, the characteristic function of a fuzzy set is allowed to have values between 0 and 1, which denotes the degree of membership of an element in a given set. Hence a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \in X\} \tag{3.2.1}$$

Where $\mu_A(x)$ is called the membership function (MF) for the fuzzy set A. The MF maps each element of X to a membership grade value (between 0 and 1). Usually X is referred to as the universe of discourse or simply the universe. The MF generalized as the bell MF (or the bell MF) is specified by three parameters $\{a_i, b_i, c_i\}$ and defined as follows [8, 32]:

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (3.2.2)$$

Where the b is usually positive value. A desired bell MF can be obtained using a proper selection of the parameter set $\{a_i, b_i, c_i\}$. During the learning phase of ANFIS, these parameters are continuously changing in order to minimize the error function between the target output values and the calculated ones [33-34].

The proposed neuro fuzzy logic of ANFIS model is a multilayer neural network-based fuzzy system. Its topology is depicted in Figure 1, where a total of five layers are used. In this connected structure, the input and output nodes represent the training values and the predicted values, respectively. In the hidden layers, there are nodes functioning as MF and rules. The benefit of the architecture is that it eliminates the disadvantage of a normal feed forward multilayer network, where it is difficult for an observer to understand or modify the network.

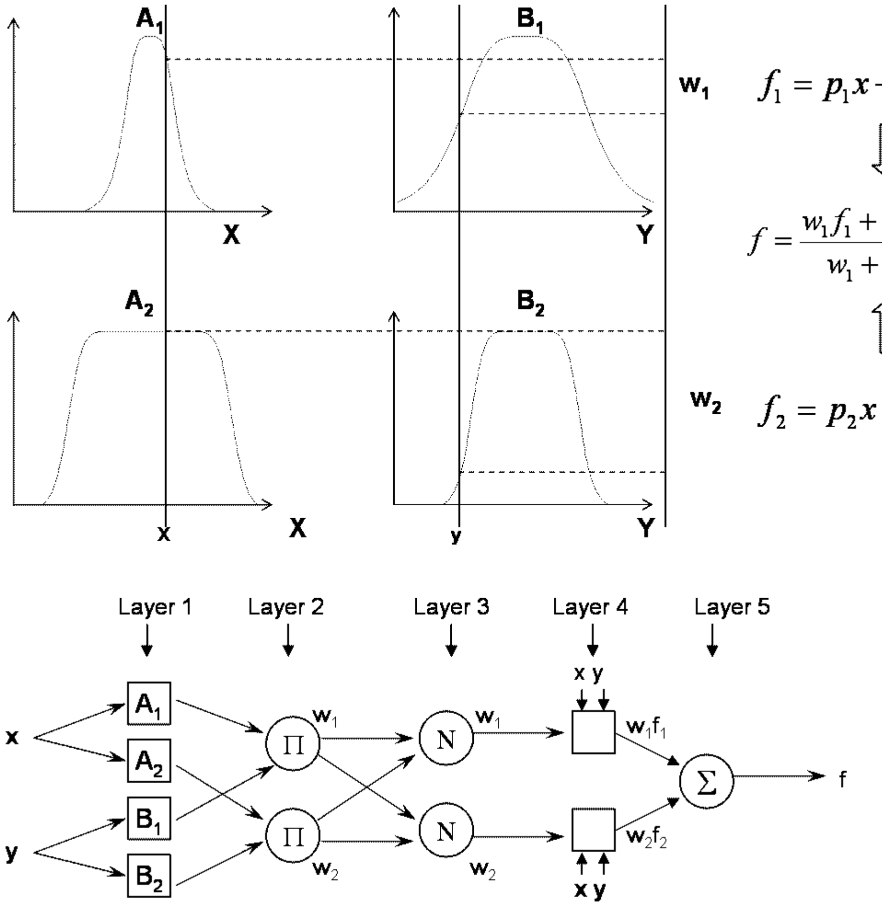

Figure 1: An illustration of the reasoning mechanism for a Sugeno-type model and the corresponding ANFIS architecture

For simplicity, it is assumed that the fuzzy inference system has two inputs x and y, and one output. Using a first-order Sugeno fuzzy model, [35] a common rule set with two fuzzy if–then rules is defined as:

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$ (3.2.3)

Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$ (3.2.4)

Each layer of ANFIS model has different nodes, and where each node is either fixed or adaptive [9]. The different layers with their associated nodes are described below:

Layer 1: Every node i in this layer is an adaptive square node with a node function:

$$O_{1,i} = \mu_{A_i}(x) \quad for \ i = 1, 2, or \ O_{1,i} = \mu_{B_{i-2}}(y) \quad for \ i = 3, 4, \qquad (3.2.5)$$

Where x - is the input to node i and A_i - is the linguistic label (small, large, etc.) associated with this node. In other words, $O_{1,i}$ is the membership function of a fuzzy set A_i and it specifies the degree to which the given input x satisfies the quantifier A_i. Usually $\mu_{A_i}(x)$ is set as a bell-shaped curve with a maximum equal to 1 and a minimum equal to 0, such as the generalized bell function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}} \qquad (3.2.6)$$

Where a_i, b_i, c_i is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thereby exhibiting various forms of MF on linguistic label A_i. Parameters in this layer are referred to as premise parameters [9].

Layer 2: Every node in this layer is a circle node labelled ∏, which multiplies the incoming signal and sends the product out:

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \ i = 1, 2. \qquad (3.2.7)$$

Layer 3: Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, \ 2. \qquad (3.2.8)$$

For convenience, the outputs of this layer are be referred to as normalized firing strengths [9].

Layer 4: Every node i in this layer is an adaptive square node with a node function:

$$O_{4,i} = \overline{w}_i \cdot f_i = \overline{w}_i (p_1 \cdot x + q_i \cdot y + r_i) \qquad (3.2.9)$$

Where: $\overline{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set in this layer. Parameters in this layer are referred to as consequent parameters [9].

Layer 5: The single node in this layer is a circle fixed node labelled ∑ that computes the overall output as the summation of all incoming signals [9]:

$$overall \ output = O_{5,i} = \sum_i \overline{w}_i \cdot f_i = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \qquad (3.2.10)$$

3.3 Discriminant model

The discriminant model involves the linear combination of two or more independent variables that differentiate between priori defined groups. The model takes a set of k-dimensional characteristics from the observed data falling in two groups. First the matrices X_1, X_2 are defined where the rows of each X_i represent a series of k-different characteristics of the members of each group, such as success or failure group. The first step is the calculation of the means $\overline{X}_1, \overline{X}_2$ and the variance-covariance matrices $\hat{\Sigma}_1, \hat{\Sigma}_2$ of the two groups. The second step is the calculation of the pooled variance by the following formula where n_1, n_2 represent the population size in group 1 (success) and group 2 (failure):

$$\hat{\Sigma} = \left(\frac{n_1 - 1}{n_1 + n_2 - 2} \right) \hat{\Sigma}_1 + \left(\frac{n_2 - 1}{n_1 + n_2 - 2} \right) \hat{\Sigma}_2 \qquad (3.3.1)$$

The third step is the estimation of the coefficient vector by the formula:

$$\hat{\beta} = \hat{\Sigma}^{-1}\left[\overline{X}_1 - \overline{X}_2\right] \tag{3.3.2}$$

By using the vector $\hat{\beta}$, every new data set is classified according his characteristics to success or failure group. The value of each $\hat{\beta}x_i$ is calculated for every new data set. If this value is closer to $\hat{\beta}\overline{X}_1$ than to $\hat{\beta}\overline{X}_2$, the data set x_i is classified to the success group, rather than to the failure group [30].

3.4 Logit Regression

In the logit analysis, the following relation between the probabilities, p_i of the binary dependent variable y_i is used between the value zero or one, for the set of k explanatory variables x :

$$p_i = \frac{1}{1+e^{-[x_i\beta+\beta_0]}} \tag{3.4.1}$$

The estimation of the parameters β, β_0 is maximized using the following log-likelihood function Λ with respect to the parameter vector, β, according to the next formula where y_i represents the observed discrete outcomes:

$$Max\Lambda = \prod (p_i)^{y_i}(1-p_i)^{1-y_i} \tag{3.4.2}$$

If the estimated probability value, p_i ,> 0.5, then p_i is coerced to 0, and is classified as a success. For values ≤ 0.5, p_i is coerced to 1and classified as a fail [30].

3.5 Probit Regression

Probit models use the cumulative Gaussian normal distribution instead of logistic function, for calculating the probability of being in one group or not:

$$p_i = \Phi(x_i\beta+\beta_0) = \int_{-\infty}^{x_i\beta+\beta_0} \phi(t)dt \tag{3.5.1}$$

Where the symbol Φ is simply the cumulative standard distribution, while the lower-case symbol, ϕ represents the standard normal density function [30].

3.6 Weibull Regression (Gompit)

The Weibull distribution, sometimes called Gompit, is an asymmetric distribution, strongly negatively skewed, approaching zero only slowly, and 1 more rapidly than the probit and logit models. It is calculated by the follow formula:

$$p_i = 1-\exp(-\exp(x_i\beta+\beta_0)) \tag{3.6.1}$$

This distribution is used for classification in survival analysis and comes from “extreme value theory’ [30].

4. Data preprocessing and variable selection

The data was collected through a completed questioner form of 167 hotel companies that introduced a new tourism services to their guests. Thirty of the questioner forms revealed that the new service launch was a failure and therefore classified as 1; the remaining137questioner forms indicated the launch was a success and therefore are classified as 0.Thetransformed data (0 or 1) data is then used to train and validate the models. It is scaled in order to facilitate the nonlinear estimation process and to avoid underflow or overflow problems. The Helge Petersohn scaling function is used to scale the data between 0 and 1 [30]. The process transforms a variable x_k to z_k and is calculated by the following formula:

$$z_{k,t} = \frac{1}{1+\exp\left[\left(\frac{\ln\left[\overline{z}_k^{-1}-1\right]-\ln\left[\underline{z}_k^{-1}-1\right]}{\max(x_k)-\min(x_k)}\right)\left[x_{k,t}-\min(x_k)\right]+\ln\left[\underline{z}_k^{-1}-1\right]^{-1}\right]} \tag{4.1.1}$$

The transformed and scaled date sets are spit into training and the validation sets. The training set is used to build the logic of the model and the validation is used validate the model. The validation set is never used in the process when the algorithm is run. The split value is 0.5 which means that almost 50% of the data (84 samples) is used for training and the remaining 50% (83 samples) is used for validation. The splitting method ensures that the training and validation sets have the same number proportionally of success and failed new services. That is particularly ideal when the count of failed category is small.

Each data set consists of 20 basic variables and 104 sub-variables based on the Like rt 5-point scale. Table 1 presents the 20 variables and their sub-variables.

Table 1: Input variables and items of each variable.

Number	**Symbol of variable**	**Name of variable**	**Number of sub-variables**
	E		
1	E1	Identification of clear Strategic Action Plans	6
2	E2	Idea Generation	5
3	E3	Preliminary Allocation of Idea	4
4	E4	Preliminary Market Assessment	9
5	E5	Preliminary Technical Assessment	4
6	E6	Market Research	8
7	E7	Business Analysis	8
8	E8	Creation of the Dysfunctional Group	4
9	E9	Planning & Development of the new Service	4
10	E10	Procedure	4
11	E11	System's Planning & Assessment	4
12	E12	Staff Training	4
13	E13	Pilot Sales	2
14	E14	Business Analysis before any promotion	3
15	E15	Service Launching	6
16	E16	Breakeven & Return on Investment analysis	4
17	ST	Organization	10
18	Z	Resource Allocation	5
19	H	Market Potential	2
20	TH	Market Synergy	7
Total	20		104

Additionally, Table 2 presents an example of the two items (sub-variables) within the variable Market Potential (H) and Table 3presents the seven sub-variables of Market Synergy (TH).

Table 2: example of the items (sub-variables) of the variable "Market Potential"

Market potential (H)	**1**	**2**	**3**	**4**	**5**
Has the size of the potential market been examined in depth?					
Was there a considerable sureness and optimism for the success of the service?					

Table 3: example of the items (sub-variables) of the variable "Market Synergy"

Market synergy (TH)	**1**	**2**	**3**	**4**	**5**
Was the service superior in covering the needs of the customers in comparison with the competitors?					
Has the service adjusted according the market image of the company?					
Were the customer needs understandable?					
Was the decision-making process and the customer behaviour clear?					
Was strong promotion support of the new services?					
Does the potential customer have an urgent need of the new service?					
Was the market size of the services increased fast?					

In the case of the ANFIS model, input reduction and input selection technique has been applied. The other models use the 20 variables listed in Table 1 as inputs. To apply ANFIS to construct a fuzzy inference system that could best predict the success there are two further problems to be solved.

The first problem to overcome is the data scarcity. For a single input data fitting problem of medium complexity 10 samples are usually needed to come up with a good model. Therefore, for a 20 variables-input problem, 10^{20}

= 1E+20 samples are needed. However, this is prohibitively large for any common modeling problem. For a two-input data-fitting problem, 10^2 = 100 samples are needed to yield the approximately the same performance. As there are only 167 data that corresponds to 1.6 data samples data scarcity is an important issue. A commonly solution used is to divide the data set into training and test data sets. The training set is used to model the data, while the test set is used for model evaluation. Thus, the resultant model is not biased toward the training data set and it is likely to have a better generalization capacity to new data.

The second problem to overcome is input space partitioning. The most frequently used input partitioning method is called 'Grid partitioning' and is the one used here. However, when using a first order Sugeno fuzzy model with 20 inputs, grid partitioning leads to at least 2^{20} = 1,048,576 rules, which results in (20+1) x 1,048,576 = 22,020,096 linear fitting parameters. This high number of parameters results in the model becoming unreliable for unforeseen inputs. To reduce this uncertainty, the input dimension is reduced by selecting two inputs that have predictive powers [34].

Initially, the average value of the items (sub-variables) of each variable from E1 to E16 is calculated (Table 1). Thus the 5 input variables (Eall_avg, ST, Z, Hand TH)are used to represent the average of their items. Only the two most relevant inputs as predictors are used. The method cycles through all the inputs to build a10 fuzzy inference model that is trained by the "anfis" command in the Fuzzy Logic Toolbox, where the "anfis" command utilizes an iterative least-squares optimization method to efficiently fine tune the parameters. The performance after the first epoch is usually a good index of how well the fuzzy model will perform after further training.

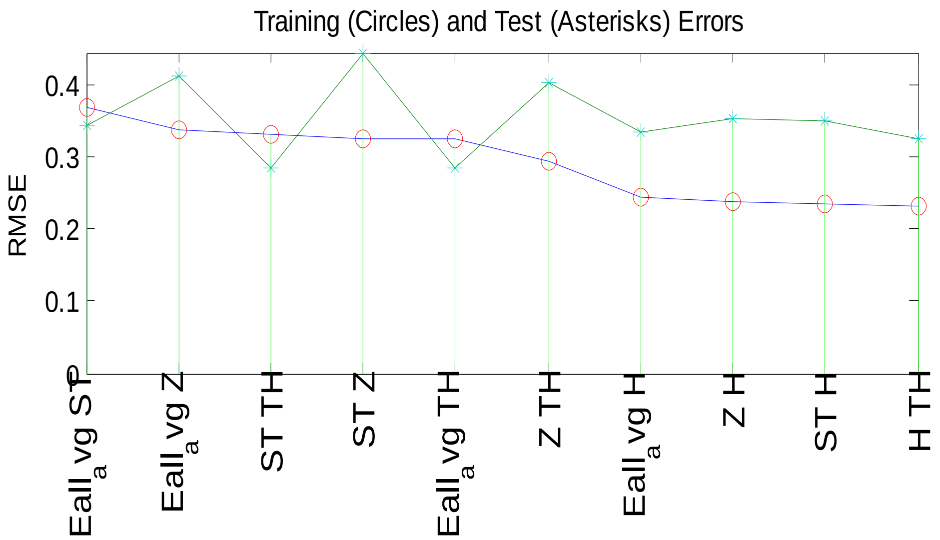

Figure 2: Fuzzy models with a single epoch of ANFIS training

The results are presented in Figure 2 with two curves representing training (circles) and test (asterisks) root mean square error (RMSE). Further, these models re-ordered according to their training error. The best model (the model with the lower RMSE) takes the variables "H"(Market potential) and "TH" (Market synergy)as input variables. In this case, both error curves are more or less consistent. This implies that the training and test data were evenly distributed across the original data set.

Once the model with two inputs has been selected, its performance is refined via extended training of 300 epochs by the "anfis" command. Table 4 describes the type and the values of the ANFIS parameters for the two input variables and the five MFs per input. The input selection technique that has been used, has reduced the fuzzy rules to 25.

Table 4: ANFIS parameter types and their values used for training

ANFIS parameter type	Value
MF type	Gauss
Number of linguistic variables (MFs)	5
Output MF	Linear
Number of Nodes	75

Number of linear parameters	75
Number of nonlinear parameters	20
Total number of parameters	95
Number of training data pairs	84
Number of evaluating data pairs	83
Number of fuzzy rules	25

4. Performance measures and experimental results

This section examines the performance of all six computational models. There are many metrics that can be used to measure the performance of a classifier or predictor; different fields have different preferences for specific metrics due to different goals. The following metrics are used to test the performance of the models:

a) False positive (FP) error or error type I takes place when the dependent variable incorrectly is labeled as 1 (failed), with $\hat{y} = 1$ when, $y = 0$. In fact, a succeed service is classified as failed [Rate of FP=(number of false positive/ number of validation samples of class 0)*100].

b) False negative (FN) error or error type II occurs when the dependent variable takes the value $\hat{y} = 0$ when $y = 1$. In fact a failed services is classified as succeeded [Rate of FN=(number of false negative/ number of validation samples of class 1)*100].

c) False weighted average error is the average of the two above errors percentage, with the weight set at 0.5[(false positive*0.5+false negative*0.5)*100].

d) True positive (TP) or accuracy of class 0 [Rate of TP=(correct classifications/ number of validation samples of class 0)*100].

e) True negative (TN) or accuracy of class 1 [Rate of TN=(correct classifications/ number of validations samples of class 1)*100].

f) Accuracy of both classes weighted [(true positive of class 0*0.5 + true negative of class 1*0.5)*100].

g) Overall accuracy [(accuracy of class 0+ accuracy of class 1/ total number of validation samples) *100] which measures the fraction of all services that are correctly categorized.

The odds ratio is the ratio of the odds of a service classified as 0 (success) to the odds of a service classified as 1 (fail). That is to say: (OR)=(TP/FP)/(TN/FN) =(TP×FN)/(FP×TN). An odds ratio > 1 indicates that a service is more likely to be classified as a success. An odds ratio of 1 indicates that the service is equally likely to be classified as a success or as a fail. An odds ratio < 1 indicates that a service is likely to be classified as a fail, [36-37].

Table 5: Out of sample forecasting performance

Methods	**False Positive %**	**False Negative %**	**False weighted average %**	**Accuracy class 0 %**	**Accuracy class 1 %**	**Accuracy weighted average %**	**Overall Accuracy %**	**Odds**
ANFIS	4.41	26.67	15.54	95.59	73.33	84.46	91.57	7.88
NN	7.35	33.33	20.34	92.65	66.67	79.66	87.95	6.30
Logit	8.82	40.00	24.41	91.18	60.00	75.59	85.54	6.89
Probit	10.29	46.67	28.48	89.71	53.33	71.52	83.13	7.63
Weibull	11.76	46.67	29.22	88.24	53.33	70.78	81.93	6.56
Discriminant	17.65	53.33	35.49	82.35	46.67	64.51	75.90	5.33

Table 5 presents the results of the out of sample forecasting accuracy for the 6 models. In the case of the ANFIS model, the out of sample percentage error of false positive (true but rejected it) of4.41%,a false negative (false but accepted) of 26.67% and the false weighted average percentage of the wrong classification of both classes is 15.54%. The false weighted average error is the average of the two percentage errors, with the weight set at 0.5.The accuracy of class 0 (success) is 95.59%. The accuracy of class 1 (fail) is 73.33%. The average weighted accuracy of both classes is 84.46%. The overall accuracy of the total number of samples for the two classes is

91.57%. Note also the odds ratio of 7.88 is greater than 1 indicating that a new service has odds of 7.88 times greater of being classified correctly in class 0 (success).Accordingly, the results for NN, Discriminant, Logit, Probit and Weibull regression models are presented.

Among all the six computational models, the ANFIS model is shown to have the highest overall accuracy, followed by the NN model and then the linear models. This would suggest, in terms of forecasting accuracy and odds, the incorporation of hybrid techniques provides a significant advantaged. This advantage may be attributable to the fact that the hybrid strategy affects the forecasting performance relative to the NN models. This is because the initial weights were not randomly set in the ANFIS model as they were set in the Neural Networks model. Another reason for this outcome may be related to the fact that ANFIS (as a class of non-linear forecasting model) can capture nonlinear patterns hidden in the data set due to the fuzzy rules-based inference mechanism inherent to the model.

The Logit model overall performance (85.54%) is close to NN performance (87.95%) this may be due to their similar functions. The other three linear models perform to a lesser extent: (81.33%) for the Probit model, (81.93%) for Weibull regression model and (75.90%) for the Discriminant model. This would indicate that nonlinearity and structural knowledge representation of the ANFIS model, and the input selection technique, provide some advantage when compared to the other 5 forecasting models.

5. Conclusions and Future Work

In this paper a novel ANFIS model has constructed to forecast the success, or failure of a new service lunched in the hotel sector. The data sets used originate from various indicators within newly lunched hotel services. According the binary the classification separated the data sets into either a success group or a fail group. This work extends the application domain of neuro-fuzzy models to tourism forecasting thus providing a prediction tool for tourism decision makers. The tool reduces the risk of the lunch a new service that a hotel faces due to the uncertain business environment and competition. In addition the tool narrows the gap between academics and practitioners by providing an efficient and accurate tool for the end users that can be leveraged to avoid the cost incurred by failure of a newly launched service.

The ANFIS model results were compared (used the same data sets)with a Neural Network using genetic algorithms and four alternative traditional classification methods (Discriminant, Logit, Probit and Weibull) for estimation, and out of sample evaluation. The ANFIS outperformed the neural network model trained by genetic algorithms and the other models in terms of the overall accuracy as it gives 91.57% correct classification.This work is largely consistent with work by Zhu and Wei [38], Mehdi and Mehdi [39], Taskaya and Casey [40] and Yu et al [41], all of whom argue for the superiority of hybrid models for accurate futures forecasting.

It is well known that neural networks cannot adequately explain it conclusion process, however combining fuzzy logic with neural networks a limited explanation of the neural network can be gained through membership functions and the use of rules in the inference processing. The methodology described here allows for the proper estimation of the success of a new service in the hotel sector without the need of any presumptions.

Further research is indeed in the use of different training algorithms for training the Neural Network model. For exampling; increasing the number of hidden layers, neurons and weighting the coercion point to a value below, or above, 0.5, or indeed expanding the coercion point to a ± valve that reflects the combined false and positive error value. These three additions may be tested and evaluation with the current data set, or tested against a different data sets obtained from another service areas. A comparative study with other models such as support vector machines and fractal analysis would be helpful. In addition the implementation of K-fold cross validation should also be examined to explore influences on model the prediction. It may also be useful to explore input selection or dimension reduction techniques such as principal component analysis and factor analysis. Finally, development of the MATLAB® software interface to increase the ease of use and online availability should be considered.

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