The Development and Comparing the Performance of Temporal Fuzzy Neural Network Technique and Temporal Fuzzy Decision Trees Case Study of Suitable Thai Elderly Tourists

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Abstract

The purpose of this research is to present a solution to change the value of the temporal fuzzy attribute. A model with data mining technique was developed to solve the problems involved with an effect to the suitability of the decision making of Thai elderly in various tourist destinations in Thailand. This model based on the import factors with the crisp value and fuzzy linguistic term. A temporal fuzzy database system with a design in the Conceptual Meta Schema was applied to collect information in the form of temporal fuzzy attributes. Moreover, this model used a temporal fuzzy attribute matching technique, which consists of the first format of the crisp and fuzzy linguistic term, and the second pattern of the fuzzy linguistic term, and the fuzzy linguistic term expression. The replica models developed between the Temporal Fuzzy Neural Network (TFNN) and the Temporal Fuzzy Decision Tree (TFDT), were compared. The result shown that performance values of the TFNN model was the most valuable, with accuracy value, precision value, recall value and f-measure at 88.9%, 79.0%, 88.9% and 83.7%, respectively. The TFNN model was a structure of 24-3-2, with momentum 0.2, and the learning rate value 0.3. This model provided a form of learning and testing cross-validation folds = 5.

Keywords: Temporal Fuzzy Decision Tree (TFDT), Temporal Fuzzy Neural Network (TFNN), Temporal Fuzzy Attribute Matching, Elderly Tourists

Introduction

The information of the Institute of Population and Social Research, Mahidol University has revealed that Thailand is currently an ageing society because a proportion of the Thai population aged 65 years and over had more than 10% of the total population (over 65 million people). Thailand had the highest share of elderly people of Association of South East Asian Nations (ASEAN) countries. While the ageing population of Singapore and Indonesia had approximately 9% and 6% respectively. When considering tourism activities, the elderly Thai people will be appreciated to travel to various places in Thailand. Therefore, these older people are considered as the target groups that the tourism business is interested in, because they have purchasing power without time restrictions. We will find that the elderly's tourism has many obstacles caused by several factors, such as health, physical, and financial status. Therefore, it is difficult to determine which tourist attraction is right. Many research have presented the use of data mining techniques in various fields, such as analyzing tourist attractions in Guilin city (Guoxia, & Jianqingm, 2009) and group of tourists and the design of goods for tourists (Aghdam, Hee, & Sim, 2014; Hua, 2016; Shapoval, Wang, & Shioya, 2018). In addition, data mining techniques were applied in conjunction with Geographic Information System (GIS) for the decision-making of travel under time and distance factors (Pasichnyk, & Artemenko, 2015), as well as the optimization of search for tourist attractions (Huang, & Ling, 2015; Jieh, R. C., & Betty, C. ,2015).

From the research mentioned above, we found that these research only used the information which takes place in the past. Consequently, the travel advice is not possible to assess the suitability of the travel planning for the elderly. Particularly, if a value of tourist information is unchanged in time, it will not be able to solve problems to correctly determine the decision for the elderly. When the value of the import factor is changed. For example, the cost of travel for the historical park of Ayutthaya. The duration between 1/12/2550 and 1/12/2561 is a high cost whereas duration between 1/12/2561 and 31/12/9999 is a lower cost. The values of both periods of time can be specified in other ways, for example, a "high cost" can be identified as an expense with a normal value (e.g. 5,000 bahts). Thus, this research is interested in applying data mining technologies (Pang, Michael, & Vipin, 2006; Richard, & Michael, 2003) to the decision-making process to find the best choice for elderly people under different conditions of each place, as well as factors associated with elderly people. This can be alternative for tourist attraction. This research developed the models by comparing the TFNN and the TFDT techniques. The obtained results from the appropriate models are used as rules to generate an embedded code under the functionality of the application in a Responsive Web Application. The users can fill in the system to process the analysis of the appropriate travel decision.

Methods and Materials

1. Selection of input attributes using the Pearson's correlation analysis

The tourism information of Thai elderly was collected consisted of 1,520 males and 1,800 females in the period of time between 1/11/2559 and 31/8/2560, and was used as an import factor to create a model. A comparison between the TFNN and the TFDT techniques, was runs under the use of 3,320 samples. The storage has a total of 12 independent variables, which have two types of characteristics. The first format is an attribute in a qualitative manner consisting of 7 attributes, such as tourist attractions, the elderly's body movement, and so on. The second pattern has a quantitative appearance, which includes 5 attributes, such as, travel costs and age, and so on. The relationship between an independent attribute and a variable based a dependent variable, was used to produce a Dummy variables to change the appearance of the quality variable to a quantitative variable. This research have determined the same value as G-1, when G is the number of groups of variables (as Table 1). The variable is a dichotomous variant with a new set of G-1, with the G5 group selection (i.e. heart disease) as a reference group to use as a comparison group.

Table 1 The Dummy variable coding of the disease variables.

Group	**Disease type**	X_1	X_2	X_3	X_4
G1	Diabetes	1	0	0	0
G2	High blood pressure	0	1	0	0
G3	Weakness Muscle disease	0	0	1	0
G4	Osteoporosis	0	0	0	1
(Reference) G5	Heart disease	0	0	0	0

This research has been used to analyze the relationship between the furnace variable as well as the prediction variable with Pearson correlation coefficient technique, where we have determined that the

"Suitability" is a variable based. The Pearson's correlation coefficient (r) was calculated as in the equation 1. A selection of the forecast variables that are converted into a quantitative variable format, which is selected from the value $0.1 \leq r \leq 1.0$ in the manner of variation by $-0.1 \leq r \leq -1.0$ respectively.

$$r = \frac{(1/N-1)(\sum XY-((\sum X)(\sum Y)/N))}{S_x S_y} \qquad (1)$$

where r is Pearson's correlation coefficient value, N is the number of samples in an attribute, S_x is the standard deviation of x value and S_y is the standard deviation of y value.

Table 2 A sample of variables calculated by using the Pearson's Correlation Coefficient

Attribute	Pearson values	Result meaning
Sex	-0.263117406	Both variables are inverse
Age	0.316227766	The two variables are variable
$Status_i$	0.240164904	The two variables are variable
$Domicile_i$	0.278243337	The two variables are variable
$Career_i$	0.117444044	The two variables are variable
$Disease_i$	-0.216097462	Both variables are inverse
$Body_i$	-0.591700439	Both variables are inverse
Saving	0.193649167	The two variables are variable
$Province_i$	-0.400802408	Both variables are inverse
$Travel_i$	-0.297221022	Both variables are inverse

2. Designing the Temporal fuzzy database using with Natural language Information Analysis Method (NIAM)

The collected information resembles in the normal attribute and the temporal fuzzy attribute. The concept of data storage based on Meta-knowledge Base and conceptual Schema was designed with NIAM technique. The Meta-knowledge Base was designed under the temporal fuzzy attribute and was mapped to relation schema. Then, this relation schema was used as a database in relational database (as Picture 1), which stored the value of fuzzy attributes (Chittayasothorn, 2009; Nijssen & Halpin, 1989). For example, travel expenses were stored in the sequence time (as table 1) displayed with a "Low" value, and (as Table 2) is displayed as both the current time, it is stored with composite trapezoidal rule. We determined that the words (i.e. Low, Medium and High) were fuzzy attribute value. We have given it a High Medium Low and fuzzy attribute value, respectively.

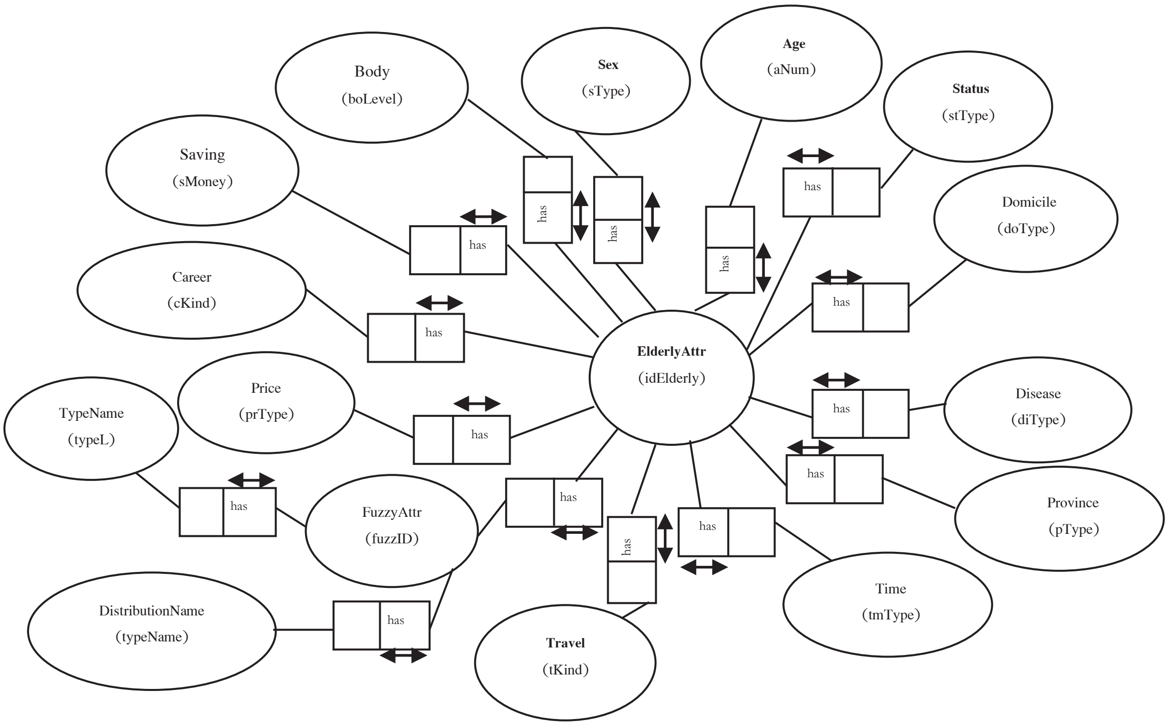


Figure 1 A sample of the Meta knowledge based on the conceptual schema

3. Temporal fuzzy attributes

The most common research demonstrated that the value of an attribute in a normal value, such as the cost of travel, was expressed as a number. For the value of the import data used in this research, if such an event occurs, under that is a time sequence of time. Then, we can identify the characteristic values or values in Fuzzy linguistic characteristics (Zimmermann, 2001), Crisp in a term has a specified value can be in the form of numbers, such as travel expenses, a number of 2,000 baht and expenditures can be specified in a manner ~~such~~ as ″Low″ that Fuzzy is equal to 2,000 baht a time interval [1/12/2550-1/12/2560, [1/12/2560-31/12/9999) time interval), and is equal to 4,000 baht. We can show you a pattern characterized by temporal attribute details are fuzzy (as in Figure 2 and equation 2 and 3, respectively). Thus, the format of the attributes in this research was represented as in the table 3 and 4, respectively.

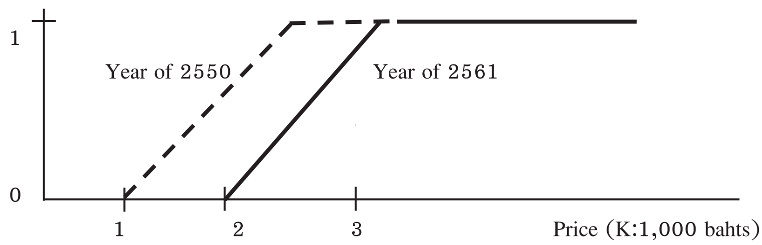


Figure 2 The meaning of travel costs using Price is “Low” at the years of 2550 and 2561.

$$T(x;1K,3K)=\begin{cases}0 & if\ x<1K\\ (x-1)/(3-1) & if\ 1K\le x\le 3K\\ 1 & if\ x>3K\end{cases} \qquad (2)$$

$$T(x;2K,5K)=\begin{cases}0 & if\ x<2K\\(x-2)/(5-2) & if\ 2K\le x\le 5K\\1 & if\ x>5K\end{cases} \quad (3)$$

Table 3 The value of Temporal Fuzzy Linguistic Term of attribute Price is "Low" of travel costs.

LabelName	fAttrName	Type	Distribution name				Valid time	
			∝	β	γ	δ	fromDate	toDate
Price	Low	Trapezoidal	4K	7K	10K	12K	1/1/2560	31/12/9999
	Low	Trapezoidal	2K	5K	7K	9K	1/1/2550	1/1/2560
	Low	Trapezoidal	1K	2K	4K	6K	1/1/2540	1/1/2550

Table 4 The value of Temporal Fuzzy Linguistic Term of attribute Price are "Low", "Medium" and "High" of travel costs.

LabelName	fdAttrName	Type	Distribution name				Valid time	
			∝	β	γ	δ	fromDate	toDate
Price	Low	Trapezoidal	4K	7K	10K	12K	1/1/2560	31/12/9999
	Medium	Trapezoidal	7K	12K	15K	19K	1/1/2560	31/12/9999
	High	Trapezoidal	10K	14K	17K	25K	1/1/2540	31/12/9999

4. The temporal fuzzy attribute matching technique

4.1 The Fuzzy attribute matching

The similarity between attribute was measured by calculating from a mathematical equation that has a characteristic of two attributes as follows:

Format 1: Calculating the similarity between Fuzzy linguistic term and Fuzzy linguistic term with the overlap width $(|w_{b1}-w_{b2}|\le c_1-c_2\le w_{b1}+w_{b2})$ figure 3(a) represents the nonoverlap of the top width between A_1 and A_2. Therefore, the similarity between fuzzy sets of A_1 and A_2 was calculated as in Equation 4;

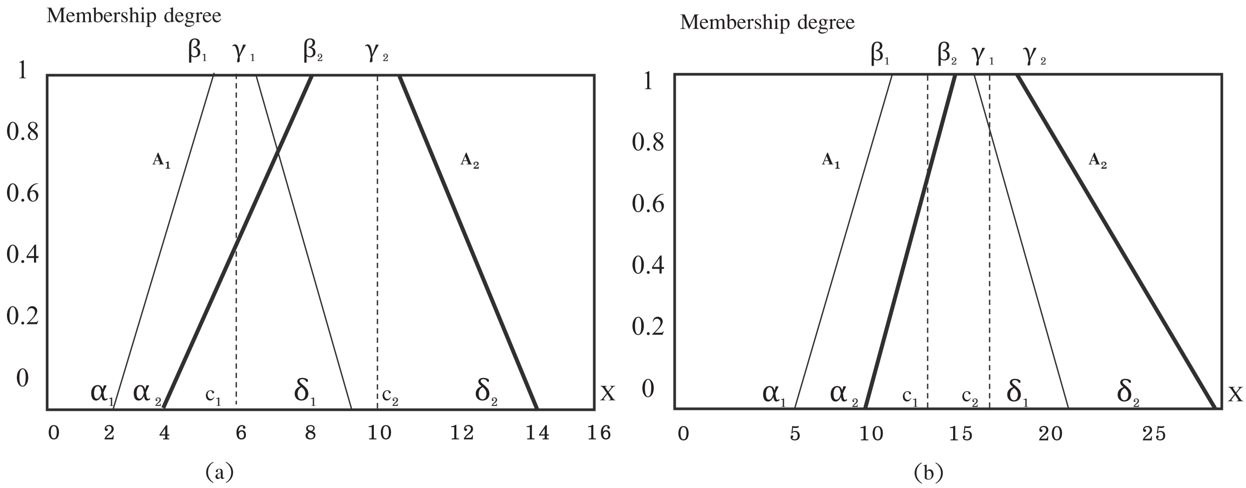


Figure 3 Represents the similarity between two fuzzy sets

$$S=h/\left(\frac{w_1+w_2}{\delta_1-\alpha_2}-h\right) \quad (4)$$

Where:

$$h = \frac{\delta_1 - \alpha_2}{\delta_1 - \gamma_1 + \delta_2 - \gamma_2}$$

$$w_i = w_{b_i} + w_{t_i} \;\; ; i = 1,2$$

$$bottom\ width\ w_{b_i} = \frac{(\delta_i - \alpha_i)}{2}, top\ width\ w_{t_i} = \frac{(\gamma_i - \beta_i)}{2}$$

Figure 3 (b) represents the overlap of the upper width between A_1 and A_2, so the similarities between Fuzzy sets A_1 and A_2 was calculated as in Equation 5;

$$S = \frac{\gamma_1 - \beta_2 + \delta_1 - \alpha_2}{\delta_2 - \alpha_1 + \gamma_2 - \beta_1} \quad (5)$$

Format 2: Making Fuzzy attribute matching between Crisp value and Fuzzy linguistic term to measure the level of membership degrees, which can be calculated as follows: (as of Equation 6)

$$\mu(x: \alpha, \beta, \gamma, \delta) = \begin{cases} 1\ when\ \beta \le x \le \gamma \\ 0\ when\ x \le \alpha\ or\ x \ge \delta \\ \dfrac{\alpha - x}{\alpha - \beta}\ when\ \alpha < x < \beta \\ \dfrac{\delta - x}{\delta - \gamma}\ when\ \gamma < x < \delta \end{cases} \quad \text{Where } x \text{ is crisp value} \quad (6)$$

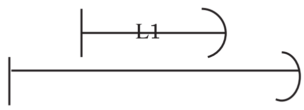
4.2 Temporal Fuzzy attribute matching

This section presents the principle of the time change of fuzzy attribute in lifespan format (Tanawong, 2017). The lifespan time is a reference to a start time and an end time, which is the scope of valid time point. This research was interested in using the format of the lifespan under a time reference that resembles two patterns:

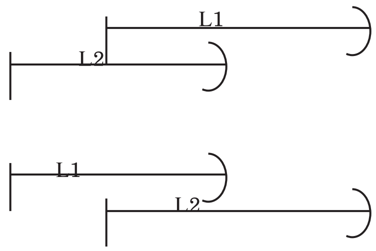
The pattern 1. A current time format was used to reference data in the current times.

The Sequence time was used to reference every period specified by the 4 styles of the following period:

Case1 1: L1 interval is a part of the L2



Case 2 and Case 3: Intervals of L1 and L2 have some overlap



Case 4: L2 period is a part of L1

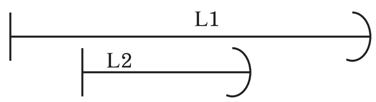
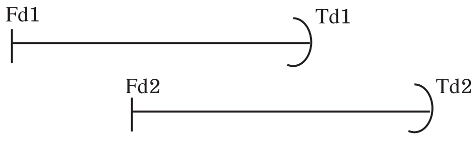


Figure 4 The time references in the Sequence time format

In this case, the use of the form of Fuzzy attribute in the 2.5.1 is that it is a time-matching process in accordance with the actual import time specified. From the time format described above, then there are 2 forms of time and Sequence characterized as Current time, respectively. In the form of time, this research has produced a matching methods with Union and Intersection, called binary temporal constructor, which is a Temporal Specification by the results as a new interval. This research need to specify the time interval time with [*Fd*1, *Td1*] and [*Fd*2, *Td*2]. They are either Overlapping or Meeting which have a format from the work of the membership function (equation 7 and equation 8, respectively).



$$\mu_{[Fd1,Td1]\cup[Fd2,Td2]}(i) = \begin{cases} 1 & if\ i = [min(Fd1,Fd2),max(Td1,Td2)] \\ 0 & otherwise \end{cases} \quad (7)$$

$$\mu_{[Fd1,Td1]\cap[Fd2,Td2]}(i) = \begin{cases} 1 & if\ i = [max(Fd1,Fd2),min(Td1,Td2)] \\ 0 & otherwise \end{cases} \quad (8)$$

5. Temporal fuzzy neural network and Temporal fuzzy decision trees

The number of attributes increased from 12 to 26, because we have changed the qualitative variable to a quantitative variable with the method of doing Dummy variables. We have refined the relationship with Pearson's correlation equation technique to find number of variables corresponding to the variable. There are 24 numbers to join factor for creating the forecast model. This research added work to the Neural Network and Decision Tree models, working under two types of data import, Crisp value and Fuzzy linguistic term. The value of the Fuzzy linguistic term was changed over time. We then matched the value of the temporal fuzzy attributes to select the node attribute for the agent to calculate the results of the prediction. We compared the TFNN model with the TFDT model to select the most appropriate model. We have divided 3,320 samples to measure the efficiency of the model. The first was a split test with 80% and 34% sample data, and 20% and 66%, respectively. The second form is Cross-validation test with K = 5 and K = 10, respectively, because it is appropriate for the number of tests and is very popular.

Results

1. Comparing results of the Temporal Fuzzy Neural Network (TFNN) and Temporal Fuzzy Decision Tree (TFDT)

A comparison of the algorithms employed during the TFNN with a 24-3-2 Momentum 0.2 learning rate of 0.3 with the J48 algorithm of TFDT. The current study found that the accuracy values, precision values, recall values and f-measure values of

Table 5 Performance of model

Classifier		Test options	Correctly	Precision	Recall	F-Measure
TREES	Id3	Percentage split20%	78.9	79.0	78.9	73.7
		Percentage split66%	75.7	80.5	75.7	82.3
		Cross validation 5-folds	81.8	81.8	81.8	81.8
		Cross validation 10-folds	80.8	80.8	80.8	80.8
	J48	Percentage split20%	78.9	79.0	78.9	73.7
		Percentage split66%	80.9	82.6	80.9	83.6
		Cross validation 5-folds	87.9	88.5	87.9	88.2
		Cross validation 10-folds	85.9	82.6	85.9	83.5
ANN	HN3	Percentage split20%	81.8	81.8	81.8	81.8
		Percentage split66%	80.8	80.8	80.8	80.8
		Cross validation 5-folds	88.9	79.0	88.9	83.7
		Cross validation 10-folds	85.7	82.2	85.7	82.3
	HN5	Percentage split20%	81.8	81.8	81.8	81.8
		Percentage split66%	80.8	80.8	80.8	80.8
		Cross validation 5-folds	85.9	79.0	85.9	83.7
		Cross validation 10-folds	85.7	82.2	85.7	82.3
	HN7	Percentage split20%	81.8	81.8	81.8	81.8
		Percentage split66%	81.8	81.8	81.8	81.8
		Cross validation 5-folds	85.9	79.0	85.9	83.7
		Cross validation 10-folds	85.7	82.2	85.7	82.3

cross-validation were at 88.9%, 79.0%, 88.9% and 83.7%, respectively, and those of cross validation fold = 5 were at 85.9%, 82.6%, 85.9% and 83.5%, respectively (Table 5). So in this research, we will create rules from TFNN for embedding code to run on the application. For the TFNN algorithm, the value of the weight value obtained from the input node with the hidden node, and between the hidden node and the output node. Some of the weight values are shown as in Table 6 and 7, respectively.

Table 6 The weight between Input node and Hidden node

List of input node	Sigmoid Node2	Sigmoid Node3	Sigmoid Node4
Threshold	0.56	0.50	0.51
Sex	-0.31	-0.33	-0.34
Age	0.68	0.71	0.73
Status	0.12	0.11	0.07
Domicile	0.44	0.45	0.51
Career=(c1:contractor)	-0.28	-0.33	-0.36
Career=(c2:teacher)	-0.08	-0.09	-0.12
Disease=(d1: Heart disease)	-0.96	-0.99	-0.96
Disease=(d2:High blood pressure)	-0.47	-0.45	-0.47
Body=(b0: Normal	0.62	0.58	0.64
Body=(b1: Short waking)	-1.43	-1.36	-1.44
Price=High(2)	0.16	-0.02	-0.04
Price=Medium(1)	-1.04	-1.05	-1.06
Price=Low(0)	-0.01	0.02	0.01
Time=Sequence (0,1)	-0.28	-0.28	-0.28
Time=Current(0,1)	-0.05	-0.04	-0.05
Saving	0.41	0.37	0.42
Province=(p2:Chiang Rai)	-0.51	-0.54	-0.56
Travel= (t3: Phu Chi Fa National Park)	-0.33	-0.32	-0.32

Table 7 The weight between a Hidden node and an Output node

List of output node	Sigmoid Node0 (No)	Sigmoid Node1(Yes)
Threshold	-2.99	2.99
Sigmoid Node2	2.66	-2.64
Sigmoid Node3	2.51	-2.57
Sigmoid Node4	2.79	-2.74

2. Calculation results for prediction of suitability of tourist sites for Thai elderly

The results for prediction of suitability of tourist sites for Thai elderly of input data (as shown in Table 8) under the TFNN model. The TFNN model will begin its operation from modifying attribute values. For example, "Price" will have to match both 15K (baths), and "Low price", "Medium price" and "High price" matches, respectively. "15K" (baths) and "High price" only. In addition, checking the time function in the form of Sequence time and set the class of Suitability attribute to 2 classes: value 1 equals "Yes" and value 0 equals "No", respectively. An example of the input data for forecasting was shown as follows:

Table 8 Samples of tourism forecasts with TFNN technique

Sex	Age	Status	Domicile	Career(c2)	Disease(d4)	Body(b2)	Price (bahts)
1	1	2	4	1	1	0	15K

Travel	Saving	Province	Time	Suitability
3	1	2	Sequence [1/12/2559-31/12/2561)	?

The first step is to select an input attribute based on a match attribute. Assume that there are multiple attributes selected under a single node in the example, the price attribute must only select 1 attribute to carry the weight attribute. Therefore, TFNN was calculated under the 24 structure of the input node, 3 of the hidden node, and 2 of the output node, respectively. The research shows only some of the attributes compared to the nodes of the Temporal fuzzy attribute, for instance, Price = “15K” (bahts) was compared with the price levels that close to the ″High″, ″Medium″, and ″Low″, respectively. A sample of 15k (bahts) with Price = ″High″ was shown as in Figure 5.

The price attribute for P1 is:

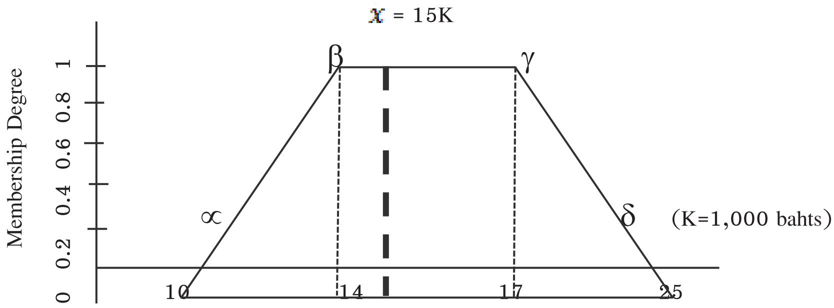


Figure 5 Comparison value of “Price” between “High” with “15K” (bahts)

Fuzzy attribute matching in the comparison of the Crisp value and the Fuzzy linguistic term can be calculated as follows:

$$\mu(x:\alpha,\beta,\gamma,\delta) = \begin{cases} 1 \ when \ \beta \le x \le \gamma \\ 0 \ when \ x \le \alpha \ or \ x \ge \delta \\ \dfrac{\alpha - x}{\alpha - \beta} \ when \ \alpha < x < \beta \\ \dfrac{\delta - x}{\delta - \gamma} \ when \ \gamma < x < \delta \end{cases}$$

From Figure 5, the value to compare between 15K (bahts) and High can be calculated and defined as follows;

--- 15K (bahts) so that $degree = \beta \le x \le \gamma$

—— High $= 1$

The computed values of 15K (bahts) which close to ″High″, ″Medium″ and ″Low″, were 1, 0.75 and 0, respectively. So we used the value of ″High″ which is equal to Sigmoid node3 = 0.157, Sigmoid node 4 = -0.018 and Sigmoid node5 = -0.040, respectively. Second, we used the time attribute from [1/12/2559-31 /12/2561] to calculate the time matching value (equation 8). Because it has intersection characteristics under the sequence time, so we calculated by case2 and case3, respectively.

Table 9 The conversion of imported data

	Sex	Age	Status	Domicile	Career(c2)	Disease(d4)
Range	0.50	0.50	1.00	2.00	0.50	0.50
Base	0.50	0.50	1.00	3.00	0.50	0.50
Norm	1.00	1.00	1.00	0.50	1.00	1.00
	Body(b2)	**Price**	**Travel**	**Saving**	**Province**	**Time**
Range	0.50	1.00	2.00	0.50	1.50	0.50
Base	0.50	1.00	2.00	0.50	1.50	0.50
Norm	-1.00	1.00	0.50	1.00	0.33	1.00

For hidden node, it will convert from attributes imported by the active function can be shown in Table 10.

Table 10 The active function for Input node-Hidden node

Input node -Hidden node					
Sigmoid node2		Sigmoid node3		Sigmoid node4	
$S=\sum_{i=1}^{n} a_i w_i$	$f(x_2)=\frac{1}{1+e^{-x_2}}$	$S=\sum_{i=1}^{n} a_i w_i$	$f(x_3)=\frac{1}{1+e^{-x_3}}$	$S=\sum_{i=1}^{n} a_i w_i$	$f(x_4)=\frac{1}{1+e^{-x_4}}$
-0.17	0.46	-0.07	0.48	-0.58	0.36

We will calculate the values to find the results. The calculated value corresponds to the result node, which are shown in Table 11.

Table 11 The active function for Hidden node-Output node

Hidden node-Output node			
Sigmoid node0 (Suitability=No)		Sigmoid node1 (Suitability=Yes)	
$S=\sum_{i=1}^{n} a_i w_i$	$f(x_0)=\frac{1}{1+e^{-x_0}}$	$S=\sum_{i=1}^{n} a_i w_i$	$f(x_1)=\frac{1}{1+e^{-x_1}}$
0.44	0.61	-0.45	0.39

We have found the inverse of $f(x_0)$ and $f(x_1)$ that is, the calculated value. (0.61 * 0.5) +0.5 = 0.81 and (0.39 * 0.5) +0.5 were 0.69 respectively. So we can conclude that the system can predict the value of the Suitability attribute which is close to Sigmoid node0 = x_0 and is set to the level value of "No".

Conclusion

This research has shown that the current Fuzzy-formatted import attributes and changes of their attribute values depending on the time changes, are an important issue for the decision-making process, like the selection of the appropriate tourism destinations. In particular, Thai elderly people require to find and select the best their destinations in Thailand. However, the tourist information of Thai elderly people are limited with the import factors (e.g. expenditures and health) which effect to the decision-making process. For example, identifying travel expenses or identifying the level of health symptoms. Therefore, the temporal fuzzy attribute was added to the data mining technique. The case study of Thai elderly was analyzed by using the TFNN and TFDT techniques to present the appropriate model. Then, the rules of the appropriate model were created and used for embedded code in the application that will help to decide the appropriate domestic destinations for Thai elderly. The current study found that the use of data mining techniques, namely the TFNN and TFDT algorithms, can create predictive models for decision-making process. The results of the TFNN algorithm yielded better performance than those of the TFDT algorithm. The format of TFNN was 24-3-2 Momentum 0.2 Learning rate 0.3. There was a division of learning and testing data. The Cross-validation folds = 5 with Accuracy value, Precision value, Recall value and F-measure were at 88.9%, 79.0%, 88.9% and 83.7%, respectively. The performance of the proposed models can help to decide the right place for the elderly from several factors that look like temporal fuzzy attribute. Next, we utilize the TFNN and TFDT with foreign elderly tourists' data to improve the models. As well as, we will increase the number of tourist attractions in Thailand to obtain the optimal model for elderly tourism is developed via data mining techniques.

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