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A decision support system for selecting convenience store location through integration of fuzzy AHP and artificial neural network

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Abstract

Location selection plays a very prominent role in retailing due to its high and long-term investments. It is very difficult to make up once an inappropriate convenience store (CVS) location has been established. The conventional approaches to location selection can only provide a set of systematic steps for problem-solving without considering the relationships between the decision factors globally. Therefore, this study aims to develop a decision support system for locating a new CVS. The proposed system consists of four components: (1) hierarchical structure development for fuzzy analytic hierarchy process (fuzzy AHP), (2) weights determination, (3) data collection, and (4) decision making. In the first component, the hierarchical structure of fuzzy AHP is formulated by reviewing the related references and interviewing the retailing experts. Then, a questionnaire survey is conducted to determine the weight of each factor in the second component, while the corresponding data are collected through some government publications and actual investigation. Finally, a feedforward neural network with error back-propagation (EBP) learning algorithm is applied to study the relationship between the factors and the store performance. The results show that proposed system is able to provide more accurate result than regression model in accuracy.

Keywords: Location selection; Artificial neural network; Error back-propagation learning algorithm; Convenience store (CVS)

1. Introduction

Location selection for a convenience store (CVS) can be defined as determination of a location, all factors affecting store costs and incomes, which will afford the owner(s) the greatest advantage taking into consideration. Also, it might be the most important decision, which will affect its subsequent success in business. The reason is that a good location can attract and be accessible to a large number of customers. Moreover, it is the top priority before any other decisions. Thus, it is very difficult to compensate for the negative influence of a bad location decision [1,2].

As today's society changes so fast, the frequency of human activities increases significantly such that the scope of our living becomes expanded. To retailing businessmen, how to attract their customers and catch the opportunities of marketplace development are the two most important issues in practice. Thus, the possibility of getting the largest profit is determined by

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location selection. For the development of retailing business, the prevalent market policy in the highly competitive market tends to be a modernized and professional joint system, such as 7-ELEVEN, which lowers the cost and raises competitiveness. In all the retailing joint systems, CVSs have the most direct contact with consumers. Therefore, this study focuses on location selection of CVSs. According to our investigation, the total number of chain CVSs in Taiwan was over 3762 in April 1997. Among these, 7-ELEVEN having more than 1400 stores is the largest. But the others are gradually trying hard to catch up. As the competition among them grows intense, finding a suitable location has thus become a critical decision since it affects the future business and long-term profitability.

The conventional approaches to location selection include managers' judgment simply based on their knowledge and experience, checklist method, analog approach, and regression model. These approaches can only provide a set of systematic steps for problem-solving without considering the relationships between the decision factors globally. Moreover, the ability and experience of the analyst(s) may also influence significantly the final outcome. Therefore, this study aims to develop a decision support system using both the feedforward neural network with error back-propagation (EBP) learning algorithm and fuzzy analytical hierarchy process (AHP) for locating a new CVS. The proposed system consists of four components: (1) hierarchical structure development for fuzzy analytic hierarchy process (fuzzy AHP), (2) weights determination, (3) data collection, and (4) decision making. In the first component, the hierarchical structure of fuzzy AHP is formulated by reviewing the related references and interviewing the retailing experts. Then, in the second component, a questionnaire survey is conducted to determine the weight of each evaluation factor, while the corresponding data are collected through some government publications and actual investigation. Finally, a feedforward neural network with EBP learning algorithm is applied to examine the relationship between the factors and the store performance, i.e. the number of visiting customers per day. The results show that the proposed system is able to provide the better result than the regression model in accuracy.

The rest of this paper is organized as follows. Section Two provides some necessary background information while the proposed system is presented in Section 3. The model evaluation results and discussion are summarized in Section 4. Concluding remarks are made in Section 5.

2. Background

The conventional methods of location selection and evaluation for a CVS include checklist method, analog approach, regression model and location allocation models, which will be discussed in the following subsections [3–5]. In addition, artificial intelligence (AI) techniques, such as expert systems, artificial neural networks (ANNs), and fuzzy sets theory used in location selection will also be reviewed.

2.1. Conventional location selection methods

The most often used methods for location selection consists of checklist methods, analog approaches, regression models and location allocation models. Checklist method, using a list of various location factors which may influence the incomes and costs of the store, evaluates systematically each of the potential locations of a specific area, compares their respective suitability indices obtained from the evaluation and finally identifies the most worthy location for investment.

An analog approach, proposed by Applebaum and co-workers [6–8], aims to determine the boundary of the interested trading area and predict the sales income of the new possible location in order to evaluate the suitability of this location. Using this method, the researcher has to find out one or several similar stores in the earlier stage and then investigate the drawing powers of these store(s) from different locations and areas. The sales incomes of the trading area and the potential location can be evaluated using these powers of the similar store(s).

The third approach, a regression model, has been applied in a variety of fields. This method is used generally for retail location analysis to determine the main factors which extensively affect business performance of a specific store and also calculate the degree of influence on business performance for each of these factors.

In principal, these models aim to allocate systematically a set of stores to render the best service for people who live dispersively in a large area as well as to maximize the overall business performance of these stores. These models usually consist of five basic elements: objective function(s), requirements, potential locations, a distance or time array, and some rules for allocation.

2.2. Artificial intelligence in location selection

Recent research has showed that the applications of ANN techniques in decision-making domain are very promising. A feedforward neural network using the golden section search method instead of the traditional steepest descent technique was presented for multiple criteria decision making [9,10]. The ANN achieved good results in evaluating and ranking alternatives. In addition, the trainability and applicability of ANN techniques to addressing general multi-attribute utility methods problems were also confirmed. In order to evaluate the capability of ANN with error back-propagation learning algorithm in decision analysis, three types of multi-attribute functions: additive, quadratic and Chebyshev were implemented and got excellent solutions for the presented problems.

One of the related approaches using fuzzy sets theory in location selection was proposed by Liang and Wang [11]. In their study, the decision makers use linguistic terms to weigh location factors. Every linguistic term is represented by a triangular fuzzy set so that the fuzzy importance of every location factor can be derived by aggregating the weights from the decision makers. Then, multiplying the fuzzy weights with their respective fuzzy location data and summing them up yield a suitability fuzzy index for each candidate location. According to the suitability indices, the most preferred location can then be targeted. Darzentas [12] proposed another fuzzy model for facility location problem. His research was to locate a facility constrained by some identified points using fuzzy accessibility measures. This method may be useful for the problem associated with social policies and non-crispy defined criteria, such as a problem, which indicates how "near" or "accessible" a facility should be.

Jungthirapanich [13] developed a decision support system which incorporated a database management system (DBMS), a linear additive multi-attribute utility method, an expert system, and graphical support. The DBMS stores the location data collected from public documents or reports. The multi-attribute utility method was used to generate a suitability index for each location. The expert system was developed to identify the top few locations and explain their advantages and disadvantages. The graphical support was to provide summary reports describing the profiles of these alternatives. However, this research can only support one decision maker. Chi et al. [14,15] modified Jungthirapanich's work and developed a neurocomputing group decision support system to support a small group of decision makers in the selection of the most appropriate location for manufacturing facilities. In this research, the ANN employs users' preferences determined via the modified analytic hierarchy process for the various location factors to identify a small subset of good candidate locations from the location database. Then the selected locations are further evaluated through computer-mediated group discussion. The experimental results reveal that the system is able to determine the top few locations from a large database.

3. Methodology

The proposed system (Fig. 1) consists of four main components: (1) hierarchical structure development of the fuzzy AHP, (2) weights determination, (3) data collection, and (4) decision making. The evaluation factors should be selected on the basis of the related papers and knowledge of domain experts. The respective data for these factors should be collected from the published government documents and on-the-spot measurements for qualitative data. Then, these data are transformed to normal form for training feedforward neural network with EBP learning algorithm. In the establishment of the ANN, data of location factors are used as the inputs of the neurons on the input layer while business performance of the store (i.e. number of visiting customers per day) is applied as the output value of the neuron on the output layer. The detailed discussion can be found in the following.

3.1. Hierarchical structure development for the location factors

The analytic hierarchy process (AHP) is one of the extensively used multi-criteria decision-making

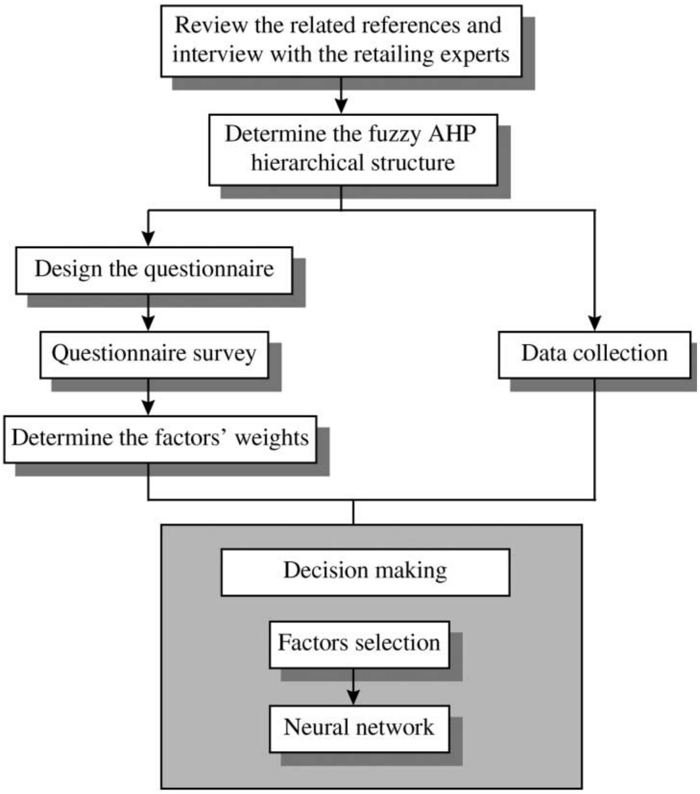

Fig. 1. The intelligent decision support system for locating a CVS.

(MCDM) methods [16–18]. One of the main advantages of this method is the relative ease with which it handles multiple criteria. In addition to this, AHP is easier to understand and it can effectively handle both qualitative and quantitative data. The use of AHP does not involve cumbersome mathematics. AHP involves the principles of decomposition, pair-wise comparisons, and priority vector generation and synthesis [19,20]. Though the purpose of AHP is to capture the experts' knowledge, the conventional AHP still cannot reflect the human thinking style. Therefore, Laarhoven and Pedrycz [21] first applied fuzzy sets theory [22,23] AHP in order to solve the objective, uncertain and fuzzy questions. In addition, Buckley [24] also presented a similar approach.

The first step of fuzzy AHP, and for the conventional AHP, is to review the related papers and interview the experts about the specific domain in order to decompose the problem hierarchically. The genetic structure of fuzzy AHP is illustrated in Fig. 2. The first level represents the overall objective/focus of the problem. The second level includes the criteria used for evaluating the alternatives, while the sub-criteria are listed in the following level.

3.2. Weights determination

After the hierarchical structure has been established, a questionnaire based on the proposed structure should be formulated. The main goal of the questionnaire is to compare pairs of element, or criteria, of each level with respect to every element in the next higher level. In [20], a nine-point scale is recommended. However, for easy answering, this study uses only the five-point scale. To integrate different experts' opinions, or triangular membership functions, the following formulas are applied:

$$L_{ij} = \min(L_{ijk}) \quad \forall k = 1, 2, \ldots, N \tag{1}$$

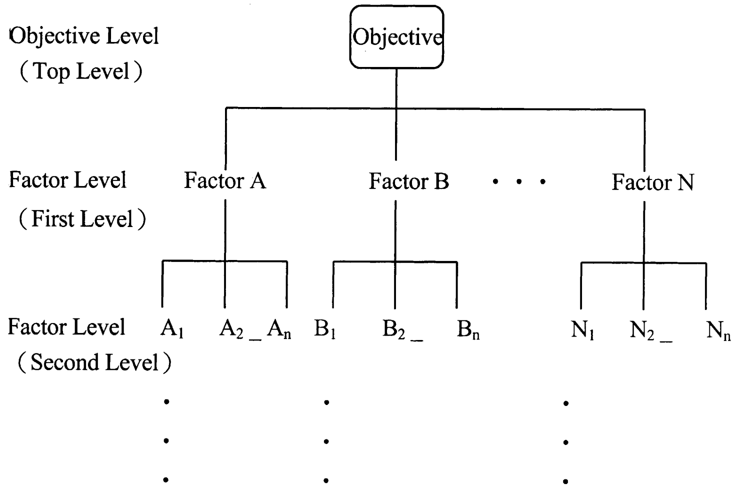

Fig. 2. The genetic structure of the AHP.

$$M_{ij} = \left(\prod_{k=1}^{N} M_{ijk}\right)^{1/N} \quad \forall k = 1, 2, \ldots, N \tag{2}$$

and

$$U_{ij} = \max(U_{ijk}) \quad \forall k = 1, 2, \ldots, N \tag{3}$$

where L_{ij}, M_{ij}, and U_{ij} are the lower width, mean and upper width, respectively. The comparisons are entered in a pair-wise comparison matrix which has the format as shown in Eq. (4).

$$\tilde{R} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \tilde{a}_{1N} \\ \tilde{a}_{21} & \tilde{a}_{22} & \tilde{a}_{2N} \\ \tilde{a}_{N1} & \tilde{a}_{N2} & \tilde{a}_{NN} \end{bmatrix} \quad \text{where}$$

$$\tilde{a}_{ji} = \begin{cases} \tilde{a}_{ij}^{-1} & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \tag{4}$$

Thus,

$$Z_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in})^{1/n} \quad \forall i \tag{5}$$

$$\tilde{W}_i = \tilde{Z}_i \emptyset (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \cdots \oplus \tilde{Z}_n) \tag{6}$$

The approach proposed by Teng and Tzeng (1993) is employed for defuzzification. For example, if there is a triangular fuzzy number

$$\tilde{A}_{ij} = (L_{ij}, M_{ij}, U_{ij}) \tag{7}$$

its defuzzified value is defined as follows:

$$DF_{ij} = \frac{[(U_{ij} - L_{ij}) + (M_{ij} - L_{ij})]}{3 + L_{ij}} \quad \forall i,j \tag{8}$$

These weights can be treated as the criteria for selecting the more important factors as the time and cost are limited.

3.3. Data collection and manipulation

Once the weight of each factor has been determined, the corresponding data of each evaluation factor should be collected in order to train the feedforward neural network. Intuitively, this can be done by reviewing the government publications and conducting actual investigations. It is without doubt that these data should be transformed in order to fit the neural network's format.

3.4. Decision making (ANN)

In this part, the feedforward neural network with EBP learning algorithm is utilized to examine the relationship between the input and output data thus obtained. The EBP learning algorithm is a kind of gradient steepest descent method used to minimize the cost function. The training procedures can be summarized as follows [25–27].

Step 1: Prepare the training samples. The samples are composed of the input vector X_p and the output vector T_p, where p is the sample number.

Step 2: Set the output range of the sigmoid activation function to be between 0 and 1. The actual data may be any real number. Thus, the actual data have to be linearly mapped onto the standardized values between 0 and 1 before they are utilized for training. For a datum L, its normal form L_n is defined as below:

$$L_n = \frac{L - L_{\min}}{L_{\max} - L_{\min}} \tag{9}$$

where $L_{\max}$ is the largest value of all the historical data of the variable; on the other hand, $L_{\min}$ is the smallest value. Similarly, the inverse of the normal form can be completed using

$$L = L_n(L_{\max} - L_{\min}) + L_{\min} \tag{10}$$

In our case, the normal form of the output from the neural network, i.e. the number of visiting customers per day, should be transformed back to the actual data by using the above formula.

Step 3: Set up all the parameters for the network. The parameters include:

1. the number of nodes on the input layer, the hidden layer, and the output layer;
2. learning rate and momentum; and
3. maximum allowable squared error for the cost function or the number of training epochs.

Step 4: Set the initial value of strength and bias for all the connections in the neural network. These values should be small, random, and nonzero numbers ranging from −0.3 to 0.3.

Step 5: Adjust all the connection strengths and biases. After calculating the cost function and mean squared error, the strength and bias for each connection have to be adjusted on the basis of the principle of minimum difference.

Step 6: Determine the stop criteria. Go back to Step 3 until the mean squared error is less than the maximum allowable squared error or the change in error is not significant during the period of certain number of training cycles.

Step 7: Test the neural network. To understand if the network has really finished learning based on the training samples, a set of testing samples is used to verify the predicted results.

4. Model evaluation results and discussion

Using the system structure discussed previously, this study investigates the 7-ELEVEN chain CVSs located in Kaoshiung city, Taiwan and analyzes the feasibility of the proposed system. The detailed discussion is as follows.

4.1. The hierarchical structure development for evaluation factors

Basically, the number of factors affecting the CVS location evaluation is quite large. Relevant references mentioned earlier show that these evaluation factors are quite complicated. After referencing [6,28–33] and discussing with the retailing experts, this study classifies them into seven dimensions: (1) population characteristics, (2) magnet, (3) store characteristics, (4) competition, (5) availability, (6) convenience, and (7) economic stability. Owing to the limitation of time, manpower, and resources, this study leaves out economic stability and adopts only six main dimensions (Table 1), which include 43 factors.

4.2. Weights determination of factors

This study employs the fuzzy AHP as mentioned in Section 3 to calculate the weight of each evaluation factor.

4.2.1. Questionnaire design

The questionnaire is constructed using the fuzzy AHP concept. There are five different degrees of evaluation used in this study, namely: (1) most important, (2) very important, (3) important (4) a little important, and (5) equally important. To avoid getting subjective results, before answering the questions, interviewees will be asked about their standard of each scale, which ranges from 1 to 10 (1 means equally important and 10 means the most important).

4.2.2. Questionnaire survey

This expert questionnaire targets on the following people:

1. business development department managers of CVSs;
2. business development department working staffs of CVSs;
3. professional consultants;
4. lecturers, and
5. CVS related institution researchers.

A total of 30 questionnaires were sent out, with 16 forms returned.

Table 1
Evaluation factors and their corresponding weights

Dimension	Weight	Evaluation factor	Weight	Evaluation factor	Weight
Competition	0.1922	Competitor's competition	0.4065		
		Competitor's store numbers	0.3455	CVS	0.3506
				Hyper market	0.3414
				Supermarket	0.3080
		Competitor's store area	0.2480		
Magnet	0.18	Crowd point	0.3544	Hospital	0.2882
				Market	0.2151
				Hotel	0.2139
				Restaurant	0.2005
				Temple	0.0785
		Culture and education organization	0.2086	School	0.4672
				Studying center	0.4161
				Library	0.1167
		Relaxation	0.2010	Recreation center	0.2595
				Department store	0.2390
				KTV, club	0.2348
				Cinema	0.1741
				Park	0.0927
				Financial organization	0.4133
		Government & business organization	0.1609	Office building	0.3166
				Government office	0.2701
		Vehicle maintenance	0.0751	Gas station	0.4394
				Parking area	0.3149
				Garage	0.2456
Convenience	0.1783	Parking convenience	0.3172		
		Pedestrian crossing	0.2798		
		Sidewalk width	0.2713		
		Road width	0.1317		
Availability	0.1648	Crowd	0.4131		
		Stations	0.2497		
		Bus stop	0.2255		
		Car flow	0.1117		
Store characteristics	0.1556	Obvious	0.7057	Located near road intersection?	0.5283
				Store visibility	0.4717
		Store front	0.2943	Store front area	0.3427
				Store front width	0.3382
				Front door width	0.3191
Population characteristics	0.1291	Community size	0.3517		
		Income/consumption	0.3493	Consumption level	0.5335
				Income level	0.4665
		Population density		Population growth rate	0.3694
			0.2990	Population density	0.3167
				Population	0.3138

4.2.3. Weights determination of each evaluation factor

The corresponding weight (Table 1) of each evaluation factor is obtained from the fuzzy AHP model by using the 16 experts' opinions. The results showed that competition is the most important factor followed by the magnet factor. Thus, rival competitiveness is the major consideration. Meanwhile, these weights can be used as the criteria for selecting the important factors if the time or cost is limited.

4.3. Data collection

The intelligent CVS location decision system is built mainly on learning historical data and predicts the performance of the new CVS. The following subsections will discuss the method used to collect and manipulate the data.

4.3.1. Sampling

This study focuses on the 138 7-ELEVEN chain CVSs located in Kaoshiung City, Taiwan. In Kaoshiung's 11 districts, 34 stores were selected randomly.

4.3.2. Definition of evaluation factors and collection method

A total of 43 factors are evaluated. The number of visiting customers per day represents the business performance of a CVS. Table 2 presents all the evaluation factors and their corresponding definitions and collection methods. All data are obtained from the actual investigation except population, population density, population growth, income average, consumption level and the number of families, which are from government publications. These factors can be categorized into the following two basic types (Table 3).

4.3.2.1. Attribute factors. During the investigation, we found that the relationships between the number of visiting customers per day and some evaluation factors, called "attribute factors", are influenced by the distance from the sampled store to any existing competitive stores. The attribute factors include government building, school, library, hospital, hotel and the like. When making the investigation, we not only conducted the number of attribute factors existing in the trading area, but completed also the drawing of their geographical locations. Moreover, the distance from each attribute factor to the sampled store and the distance from each attribute factor to the competitive store were measured.

4.3.2.2. Variable factors. Apart from the attribute factors, all other factors are called "variable factors" which are divided into three categories:

1. Those acquired from the documents published by the city government include population, density of population, growth of population, income level, consumption level, and the number of resident families.
2. Those obtained from the actual investigation include store width, store space, main door width, store's proximity to street intersection, the total area of the competitive stores, road width, and sidewalk width.
3. The number of visiting customers, and competitors, people flow, car flow, store front visibility and parking convenience, are obtained by the following methods:
   - 3.1. The number of visiting customers: Since the number of visiting customers and sales revenue are confidential, we use receipts' number to estimate the total number of visiting customers in 1 week, and then obtain the average daily number of visiting customers. For instance, 10:00 a.m., at 1 May we bought something from the sampled CVS and received a receipt. Then, 10:00 a.m., At 8 May we did it again. Difference between these two numbers on the receipts can be assumed to be the total number of visiting customers in 1 week. After being divided by 7, it can be used as the business performance of the CVS in 1 day.
   - 3.2. Competitor's ability: This factor is obtained from logistic investigation of CVS island-wide in 1996. Every CVS scores was divided by the highest one to obtain the competitor's ability score.
   - 3.3. People flow/car flow: Full usage is the chief criterion when measuring people flow and car flow. Thus, the number of bikes belongs to people flow, while the number of motorcycles belongs to car flow. During the investigation periods, 2 days were randomly selected from Monday through Friday. One hour is chosen from 9:00 a.m. to 11:30 a.m. and 1:30 p.m. to 4:00 p.m. randomly for 1 day. The other hour is selected from 7:00 p.m. to 9:30 p.m. randomly for the other day. The sum of people flow occurred during these 2 hours are the people flow. The measurement of car flow is also of the same manner.

Table 2
The evaluation factors and their corresponding definitions and data collecting method

Evaluation factor	Definition	Data collecting method
The number of visiting customers	Average daily number of visiting customers	Actual investigation
Government organization	# in the business circle	Actual investigation
Post office & finical organization	# in the business circle	Actual investigation
School	# in the business circle	Actual investigation
Studying center	# in the business circle	Actual investigation
Library	# in the business circle	Actual investigation
Hotel	# in the business circle	Actual investigation
Restaurant	# in the business circle	Actual investigation
Temple	# in the business circle	Actual investigation
Market	# in the business circle	Actual investigation
Park	# in the business circle	Actual investigation
Cinema	# in the business circle	Actual investigation
Department store	# in the business circle	Actual investigation
KTV	# in the business circle	Actual investigation
Recreation center	# in the business circle	Actual investigation
Garage	# in the business circle	Actual investigation
Parking lot	# in the business circle	Actual investigation
Gas station	# in the business circle	Actual investigation
Store front width	Size of store front width	Actual investigation
Store front area	Size of store front area	Actual investigation
Front door width	Size of front door width	Actual investigation
Store visibility	Visibility for consumers to see stores	Actual investigation
Located near intersection?	Distance between store and intersection	Actual investigation
CVS	# in the business circle	Actual investigation
Supermarket	# in the business circle	Actual investigation
Hypermarket	# in the business circle	Actual investigation
Competitor's store area	Total of competitor's store area	Actual investigation
Competitor's competition	Total of competitor's competition	Actual investigation
People flow	Total of people & bike pass over	Actual investigation
Car flow	Total of car & motorcycle pass over	Actual investigation
Station	Total of train station & bus station #	Actual investigation
Bus stop	Total of bus stop # in the circle	Actual investigation
Road width	Road width which store is facing	Actual investigation
Sidewalk width	Sidewalk width in front of stores	Actual investigation
Parking convenience	Is it easy to park around store?	Actual investigation
Pedestrian crossing	# of pedestrian crossing in circle	Actual investigation
Population	Population of the neighborhood	City publication
Population density	Population *D* of the neighborhood	City publication
population growth rate	Average yearly population growth in the latest 5 years	City publication
Income level	Average income level of the neighborhood	City publication
Consumption level	Consumption level of the neighborhood	City publication
The number of resident families	Families # of the neighborhood	City publication

3.4. Store front visibility: This is a fuzzy factor, and is therefore, determined by the following evaluation model:

Step 1: Investigate all the sampled stores' location and evaluate stores' visibility.

Step 2: Establish six evaluation standards as shown in Fig. 3. Two principle assumptions of these six cases are:

- all roads have four lanes;
- arrows and numbers mean the direction and distance, respectively, to sampled stores.

Step 3: During actual investigation, scores are adjusted according to the following four conditions:

- if the road has more than four lanes, add 1 score; if less, deduct 1 score;

Table 3
Attribute and variable factors

	Attribute factors		Variable factors	
Government organization	Market	Supermarket	The number of visiting customers	Road width
Office building	Park	Hypermarket	Store front width	Sidewalk width
Post office & economic organization	Theater	Station	Store front area	Parking convenience
School	Department store	Bus station	Store front door width	Population
Studying center	KTV	Pedestrian crossing	Store front visibility	Population density
Library	Recreation center		Store located at road intersection	Population growth rate
Hospital	Garage		Competing store area	Income level
Restaurant	Parking lot		Competition	Consumption level
Hotels	Gas station		People flow	The number of families
Temples	CVS		Car flow	

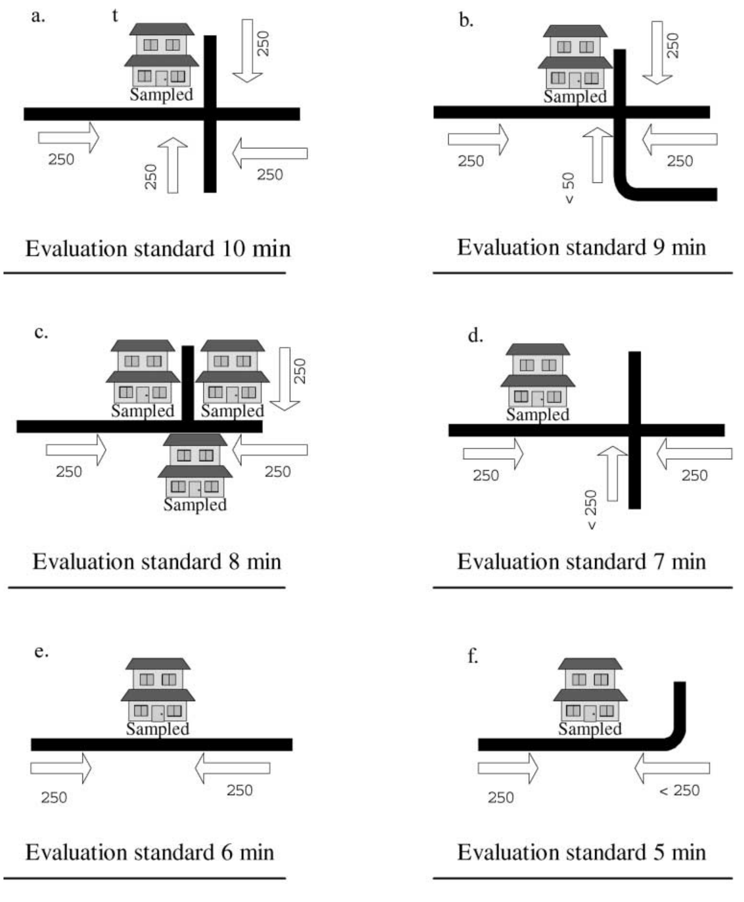

Fig. 3. Six cases for determining the competition ability.

– if the length of the road is less than 100 m, deduct 1 score;
– if the distance to the sampled store of one of the directions is less than 250 m, deduct 1 score;
– if there were trees in the middle of the road, deduct 1 score.

3.5. Parking convenience: This score is obtained by comparison. Ten is the highest score. The major evaluation conditions are listed as follows:
– availability of parking lot around sampled store in 20 m;
– availability of parking space in front of the sampled store;
– road width;
– sidewalk width.

4.3.3. Data manipulation

To make the collected data truly reflect the actual situation, we develop a data manipulation model for the attribute factors. This model involves distance and retailing competition problems of the consumer trading cost.

4.3.3.1. Distance. All the theories about retailing location, such as the Central Place Theory proposed by Christaller, Reilly's Law of Retail Gravitation, and Converse's Break Point, mentioned that the purchasing power of consumers are gradually decreased as the increasing of distance. To obtain an objective weight for distance, we completed an investigation using another questionnaire. The age backgrounds are shown in Table 4. Herein, the weight means the attraction value to the consumers. From the result presented in Table 5, it can be concluded that the intention to walk for shopping is negatively proportional to the square of distance.

Table 4
Testers' age background

	The number of persons	Percentage
1–15	1	0.21
16–25	291	60.63
26–35	109	22.71
36–45	54	11.25
46–55	23	4.79
56 and above	2	0.42
Total	480	100

Table 5
The number of persons who may walk further for shopping under different distances

Distance (m)	The number of persons	Percentage
50	242	50.42
100	120	25
150	53	11.04
200	42	8.75
250	15	3.13
Over 250	8	1.67
Total	480	100

4.3.3.2. Competition. Whether there is any competitive stores in the trading area of the sampled store will significantly influence its business performance. That means the competitive stores will attract part of the consumers and reduce relatively the number of consumers going to the sampled store. Therefore, we attempt to manipulate the data for the attribute factors according to four different situations:

1. No competitive store in the trading area: in this simple situation, the attribute factor is only affected by distance regardless of competition.
2. The attribute factor located between the sampled store and the competitive store:

   In this case, we assume:

   2.1. The distance between the attribute factor and the sampled store is D.
   2.2. The distance between the attribute factor and the competitive store is d.
   2.3. The competitive value of the sampled store is C_7.
   2.4. The competitive value of the competitive store is C_c.
   2.5. The attraction value of the sampled store on the attribute factor is A_7.
   2.6. The attraction value of the competitive store on the attribute factor is A_c.
   2.7. The weight of the attribute factor for the sampled store is W_d.

   As mentioned above, the attraction value is negatively proportional to the square of distance, but on the other hand the attraction value is positively proportional to the competitive value of the store. Thus, we can get the following formula:

$$A_7 \propto C_7 \times \frac{1}{D^2} \tag{11}$$

$$A_c \propto C_c \times \frac{1}{d^2} \tag{12}$$

$$\frac{A_7}{A_c} = \frac{C_7 \times d^2}{C_c \times D^2} \Rightarrow \frac{A_7}{A_7 + A_c} = \frac{C_7 \times d^2}{(C_7 \times d^2) + (C_c \times D^2)} \tag{13}$$

This ratio might be called coefficient of competitive attraction. It is similar to Reilly's law of retail gravitation, as the competitive value of the store is relative to the city population. Finally, data of the attribute factor for the sampled store are described as follows:

$$W_D \times \frac{A_7}{A_7 + A_c} \tag{14}$$

In other words, if an attribute factor exists, both the distance weight and the coefficient of competitive attraction should be considered.

3. The sampled store located between the attribute factor and the competitive store:

   This situation pictures that there is a competitive store further away from the consumers than the sampled store, 7-ELEVEN. We prepared a questionnaire to understand how far the consumers are willing to walk up to the competitive store bypassing the sampled store. The result (Table 6) showed that 14.17% of the consumers would walk further to the competitive store after passing by the sampled store. And 38.24% of these people would walk for an extra 10 m. Under competition, distances between the competitive stores and sampled stores can be used to calculate the competition attraction parameter. Results are presented in Table 7.

Table 7
The distance weights[a]

Distance between sampled/competing stores (m)	Weight of sampled stores	Data
$d > 50$	0.9958	(Weight of D) $*$ 0.9958
$40 < d \leq 50$	0.9833	(Weight of D) $*$ 0.9833
$30 < d \leq 40$	0.9812	(Weight of D) $*$ 0.9812
$20 < d \leq 30$	0.9666	(Weight of D) $*$ 0.9666
$10 < d \leq 20$	0.9458	(Weight of D) $*$ 0.9458
$d \leq 10$	0.8583	(Weight of D) $*$ 0.8583

[a] D represents the distance.

4. The competitive store located between the attribute factor and the sampled store:

   This situation showed that the sampled store, 7-ELEVEN, is further from the consumers than the competitive store. We also prepared another questionnaire to understand how far the consumers are willing to walk further to the sampled store bypassing the competitive store. Results are listed in Table 8. There are 39.17% of these people who would walk further to the sampled store and 60.11% of these persons would walk an extra 10 m or more.

   Under competition, distances between competing stores and sampled stores can be used to calculate the competition attraction parameters, which are shown in Table 9.

4.4. Decision making (ANN)

In this part, the historical data with both input and output data collected are applied to train the feedforward neural network with EBP learning algorithm after the data are transformed into the acceptable format (i.e. the standard form of data for neural network). The total number of samples is 34 which is also

Table 6
Distance evaluation

	Yes (68)						Will not	Total
Distance (m)	10	20	30	40	50	Over 50		
People	42	10	7	1	6	2		
Percentage/68	61.76	14.71	10.29	1.47	8.82	2.94	412	480
Percentage/480	8.75	2.08	1.46	0.21	1.25	0.42		
Percentage			14.17				85.83	100

Table 8
The number of persons who may walk further to the sampled store by passing the competitive store under different walking distances

	Yes (188)						Will not	Total
Distance (m)	10	20	30	40	50	Over 50		
People	75	55	26	5	18	9		
Percentage/68	39.89	29.26	13.83	2.66	9.57	4.79		
Percentage/480	15.63	11.46	5.42	1.04	3.75	1.88		
Percentage			39.17				60.83	100

Table 9
The weights for different walking distances that the consumers are willing to walk further to the sampled store by passing the competitive store

Distance between sampled/competitive stores (m)	Weight of sampled stores	Data
$d > 50$	0.0188	(Weight of D) $*$ 0.0188
$40 < d \leq 50$	0.0562	(Weight of D) $*$ 0.0562
$30 < d \leq 40$	0.0666	(Weight of D) $*$ 0.0666
$20 < d \leq 30$	0.1208	(Weight of D) $*$ 0.1208
$10 < d \leq 20$	0.2354	(Weight of D) $*$ 0.2354
$d \leq 10$	0.3917	(Weight of D) $*$ 0.3917

the number of sampled CVSs. Among them, thirty samples are selected randomly as training samples and the other four samples are used for testing. Since there are 34 factors, the number of inputs is also 43. Meanwhile, the output is the number of visiting customers per day for each CVS. In this study, one-hidden-layer network is considered.

In principle, the EBP learning algorithm employs on the gradient steepest descent method to minimize the cost function. Some parameters should be well set up in order to reach the global minimum. Thus, three different choices, 0.2, 0.5, and 0.8, are verified for both training rate and momentum term. The sigmoid function is employed for activation function, while the mean square error (MSE) value is treated as the stop criteria. Regarding the number of the hidden layers, the following four alternatives are tested:

1. Network 1: 7 hidden nodes = (the number of input nodes $\times$ the number of output nodes)$^{1/2}$;
2. Network 2: 22 hidden nodes = $1/2$ (the number of input nodes + the number of output nodes);
3. Network 3: 27 hidden nodes = $1/2$ (the number of input nodes + the number of output nodes) + (the number of samples)$^{1/2}$;
4. Network 4: 87 hidden nodes = 2 (the number of input nodes).

   In addition to these four networks, two different kinds of inputs are also tested:
   4.1. The input data do not consider the influence of distance and competition factors.
   4.2. The input data consider the influence of distance and competition factors.

4.4.1. ANN without considering fuzzy AHP

Table 10 illustrates the summarized results as all the factors are fed into the neural network. From the above table, two prominent findings can be observed. First, it is obvious that there is no significant effect on learning convergence during the training stage in all the various networks when considering the distance and competition problems in data manipulation. However, the MSE values of the testing samples obtained from these four networks are significantly

Table 10
The MSE values of training and testing results for different inputs

		Model 1	Model 2	Model 3	Model 4	Mean
Train	With	0.000085	0.001151	0.000409	0.023113	0.0061895
	Without	0.000067	0.000697	0.000263	0.025563	0.0066475
Test	With	0.003698	0.004878	0.001191	0.017258	0.006756
	Without	0.120939	0.154165	0.138490	0.169791	0.145846

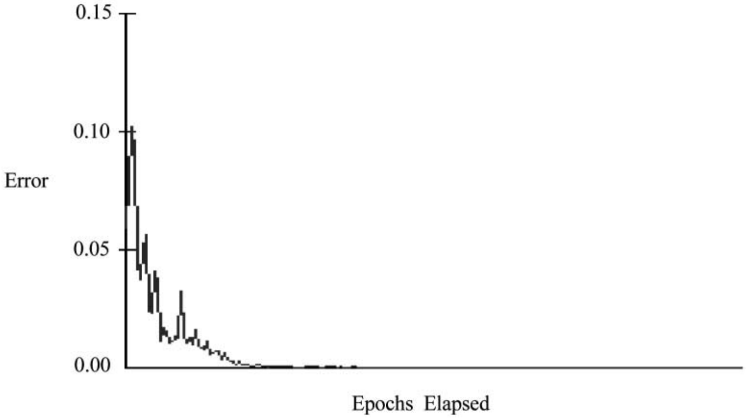

Fig. 4. Training curve for model 4.

Table 11
The testing results of four testing samples

Store number	Actual number of visiting customers	Actual ranking	Estimated ranking	Estimated number of visiting customers
1	1774	1	1	1774
2	1061	2	2	1071
3	817	3	3	817
4	1020	4	4	1011

affected by the data manipulation procedures. In other words, the input data considering both the distance and competition factors can improve the prediction accuracy of the neural networks. This result substantially contributes to the development of the decision support system for location selection for CVSs. Second, network 4, whose MSE value for training is 0 and the MSE value for testing is 0.000057, can provide the best performance among the four different networks as the training rate and momentum term are 0.5 and 0.8, respectively. Fig. 4 illustrates the training curve, while the testing results of the 4 testing samples are presented in Table 11. The MSE value is around 52 customers, while the ranking accuracy is 100%.

Regression model is also used for comparison. Its MSE value is 0.0907 which is worse than the ANN result.

4.4.2. ANN with fuzzy AHP

In the above subsection, all the 43 factors are fed into the feedforward neural network with EBP learning algorithm for training and test. However, in the real life, the work, which is time-consuming and

Table 12
The MSE values of different inputs

	All inputs		31 Inputs		14 Inputs	
	ANN	Regression	G[a]	B[b]	G[a]	B[b]
Test	0.017258	0.0907	0.027766	0.030575	0.046722	0.152363

[a] G means that 31 (14) better factors are selected based on the fuzzy AHP results.
[b] B means that 31 (14) worse factors are selected based on the fuzzy AHP results.

costly, will never be applied in the industry. Under this consideration, the results, or weights, of fuzzy AHP can be used as the criteria for selecting the important factors. Therefore, the following four alternatives are tested.

1. The 31 factors with the larger weights, (31G).
2. The 31 factors with the smaller weights, (31G).
3. The 14 factors with the larger weights, (14G), and
4. The 14 factors with the smaller weights (14B).

The summarized results are shown in Table 12. It is apparent if the inputs of higher evaluation weights are selected for the network, then its performance will be better. Thus, if the time and cost are limited, the manager can eliminate some factors with lower evaluation weights. This will not influence significantly the prediction accuracy but save plenty of valuable time and cost.

5. Conclusions

This research proposed a decision support system for locating CVSs. It is confirmed that the data manipulation procedures, which include the distance and competition factors in modifying the original historical data of the sampled stores really advance prediction accuracy of the neural network.

The evaluation weights provided by fuzzy AHP can be applied as the criteria for selecting the important factors. If the company does not have much time to collect all the data, then some less important factors can be ignored. This will not much decrease the accuracy of the result and increase significantly the incentive of using the proposed system since the managers can have the criteria for selection important factor under different situations. Table 12 has illustrated that if the more important factors are selected, then the results will not be much less than the results of including all factors.

It was also shown that the proposed approach is much better than the regression model in accuracy. Though ANN may need more training time, yet this can be done off-line. As the ANN is for real-time use, its speed is very fast. Moreover, the proposed system has been computerized. It can provide the users a very friendly environment, which can improve the usability.

In the future, we can extend the proposed system in order to consider the multiple locations simultaneously. In addition, it can be applied to different types of networks, like radial basis function network.

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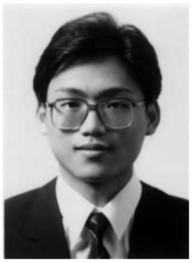

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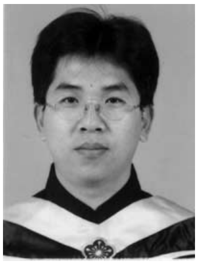

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